Intangible capital and economic growth

Chen, Wen

Intangible Capital and Economic Growth

Wen Chen

Publisher: University of Groningen, Groningen, The Netherlands

Printer: Ipskamp Drukkers B.V.

ISBN: 978-90-367-8916-5 / 978-90-367-8915-8 (eBook)

This thesis was typeset in LaTeX using Laurie Reijnder's much appreciated style file.

Intangible Capital and Economic Growth

PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. E. Sterken
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Thursday 30 June 2016 at 12:45 hours

by

Wen Chen

born on 27 May 1987
in Nanchang, China

Supervisor
Prof. Marcel Timmer

Co-supervisor
Dr. Robert Inklaar

Assessment committee
Prof. Jonathan Haskel
Prof. Matilde Mas
Prof. Bart van Ark

Acknowledgements

It reads as a prologue but what it really represents, deep down, is a closure of the past four-and-a-half years of my time as a PhD student. When I started back in 2011, it felt like I had all the time in the world ahead of me. But when I look back now, it just went by in a flash.

This thesis only carries my name on the cover, but it is a product of joint efforts of many others. Please let me start by thanking the two most important contributors to this book: Marcel Timmer and Robert Inklaar, without them this thesis would not have existed. I want to thank Marcel for his superb and attentive guidance in the completion of this thesis. Though we did not have regular meetings, whenever we sit in one I always feel encouraged and inspired by him. I am also very grateful to Marcel for his generous support for many of my conference travels and for offering me a post-doc position even before my PhD was finished. These are luxuries that not many PhDs have and I am lucky that they were in my possession. I want to thank Robert for introducing me to this field of research on intangibles and to a research network that is working on the state-of-the-art of this topic. I really appreciated all his constructive comments and timely feedback every step of the way. By working and teaching with Robert, I also learned much what makes a good researcher and teacher. Thank you Marcel and Robert, it has been an honour and a privilege to be your student.

I would like to extend my gratitude to the members of the reading committee for their valuable time and efforts to read my manuscript and share their views with me: Professors Jonathan Haskel, Matilde Mas, and Bart van Ark.

In summer 2013, I spent about 3-4 weeks at the Centre for European Economic Research (ZEW) in Mannheim, Germany for research collaboration. I want to thank Thomas Niebel and Marianne Saam for their great hospitality and fruitful cooperation on the paper, which led to my first scientific publication. I also would like to thank Wendy Li from the U.S. Bureau of Economic Analysis for various conference invitations. In particular, the opportunity to present my work at the world's largest economics conference in Boston in 2015. It was a great experience seeing the AEA meeting up close.

It goes without saying that I am thankful to many supporting staff at the university, especially to the SOM team resided at the Pavilion as well as Gemmies on the *gezellige* (I was told that this word is not really translatable as there is no English alternative that can reflect the full extent of what this Dutch word represents) 5th floor. Thank you for helping me solving all sorts of administrative issues and assisting me in all routine necessities, which are also an integral part of research.

I would like to thank Laurie Reijnders, Job van Tilburg, Zoë Zernitz and Cenkhan Sahin for their great help with the Dutch translation. Without their check, double-check and triple-check on the translation, the Dutch summary would have been unreadable and incomprehensible. I also want to thank Marianna Papakonstantinou for, among other things, being a helpful hand as my paranymph.

There are many colleagues at FEB and other faculties (some of them have left now) as well as friends from outside academia that I wish to extend my gratitude to. However, I find it rather dull and cliché to simply list all the names and there is a great risk that I may forget to mention some names that deserve my appreciation. Given these, I'd like to be somewhat unconventional by ending this section with a *personalised* space where my accidental oblivion can be rightfully corrected and my sincere appreciation can be extended to: ________________.

Last but not least, I am eternally grateful to my family. I could never have made it this far if it were not for their unconditional love, trust and support.

最后，我想感谢我挚爱的家人。正是因为你们对我毫无保留的支持，理解和鼓励让我可以顺利完成学业！谨以此书献给你们。

Wen Chen
June 2016

Contents

List of Tables

List of Figures

CHAPTER 1

Introduction

> *"Not everything that can be counted counts, and not everything that counts can be counted"*
>
> – Albert Einstein

> *"It is better to be roughly right than precisely wrong"*
>
> – John Maynard Keynes

1.1 Background

Understanding the sources of economic growth and differences in income across countries are at the heart of the economics profession. Ever since Solow (1956) and Swan (1956) developed neo-classical growth model, economists have sought to distinguish between two proximate causes of economic growth and income differences: *factor accumulation* and *total factor productivity* (TFP). The conventional wisdom that TFP accounts for the bulk of growth and cross-country income differences is challenged (e.g. Corrado, Hulten & Sichel, 2009) as the modern economy, characterised by the pervasive use of information and communications technology (ICT), is in the midst of rapid changes. As a "General Purpose Technology" (Bresnahan & Trajtenberg, 1995), ICT facilitate numerous complementary innovations which enhance firm productivity by reducing costs and by enabling firms to develop new products or improve in the intangible aspects of existing products like convenience and timeliness (Brynjolfsson & Hitt, 2000). As a consequence, business investment in traditional assets like machinery and buildings has become less important. Instead, ever more resources are shifted into investment in knowledge-based intangible assets, such as product design, marketing, and management practices, which are increasingly seen as the key creators of value for businesses.[1] The rising trend of these new types of investment suggests that the standard empirical analyses of growth based on traditional factor inputs (i.e. labour and physical capital) are missing out on an important part of investment in the 21st century and are no longer well-suited for understanding the drivers of modern economic growth.

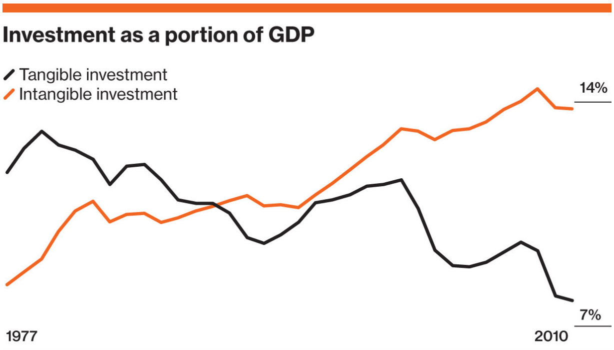
A new strand of literature emerged over the last decade aiming to correct for the way that business activities are depicted in macroeconomic data and analysis. This is done by broadening the investment concept beyond spending on physical assets. It is argued that as long as current resources are committed to provide for *future* rather than *current* consumption, any expenditures, either on tangible or intangible assets, should be capitalised and included in a country's gross domestic product (GDP) as business investment (Corrado, Hulten & Sichel, 2005). The argument gained momentum among scholars and policy makers alike and eventually led to the development of a broad scheme for categorising and measuring business intangible investment that should be included in a country's national accounts. The upper panel of Figure 1.1 provides a list of intangible assets that have been proposed by the pioneers in this research (Corrado et al., 2005). Based on this expanded conceptual framework, a growing body of work has shown that there is a clear shift in the investment composition towards knowledge-based intangible assets at the aggregate economy level (Corrado, Haskel, Jona-Lasinio & Iommi, 2012; OECD, 2013a). This is especially true for industrialised economies, such as the U.S. where intangible investment had already exceeded traditional investment in physical assets by the early 1990s and has kept on increasing over time (see the lower panel of Figure 1.1).

Economic research on the importance of intangible assets is not new, starting with research on the economic impact of investment in research and development (R&D). These studies tried to determine how R&D investment enhances the productivity of investing firms (Griliches, 1979, 1987; Mansfield, 1965) and how the newly developed knowledge could 'spill over' to other firms or industries working on related technologies (Bernstein & Nadiri, 1988; Griliches, 1992) as well as affect rivals in product markets (Bloom, Schankerman & Van Reenen, 2013). With the rapid advances in ICT in the 1980s, later research focused on the role of ICT in productivity and growth (e.g. Colecchia & Schreyer, 2002; Van Ark, O'Mahony & Timmer, 2008) and how

[1] The value of some global leading companies, such as Facebook and Microsoft, is largely accounted for by their intangible assets (Hulten, 2010). Moreover, international production fragmentation is another salient feature of the modern economy. Much research (e.g. Dedrick, Kraemer & Linden, 2010) has shown that the highest level of value creation in a global value chain is often found in activities like research and development, marketing and branding, and customer services, signifying the important role of knowledge-based capital in today's economy.

Figure 1.1: List of Intangibles Proposed and Investment Trend in the U.S.

Broad Category	Type of Investment
Computerised Information	• Software • Databases
Innovative Property	• R&D • Mineral exploration • Entertainment and artistic originals • Design and other new product development costs
Economic Competencies	• Branding (market research and long-lived advertising) • Firm-specific human capital (training) • Organisation capital (business process development)



Source: Corrado and Hulten (2014)

its productive potential could be better exploited with complementary investments in firm-specific human capital and organisational structures (Bloom, Sadun & Van Reenen, 2012; Brynjolfsson & Hitt, 2000, 2003). According to an important macroeconomic study by Basu, Fernald, Oulton and Srinivasan (2004), these complementary investments to ICT play a substantial role in explaining why productivity growth accelerated in the U.S. but slowed down in the U.K., driving a productivity gap across the Atlantic in the second half of the 1990s.

Building on the pioneering measurement work of Corrado et al. (2005), more recent literature begins to incorporate intangible assets into a standard 'sources-of-growth' framework and examine how the inclusion of intangibles affects the growth patterns of a country (e.g. Corrado et al., 2012, 2009; Fukao, Miyagawa, Mukai, Shinoda & Tonogi, 2009). In general, these studies find that intangible capital is an important source of growth: measured investment rates are higher than when only traditional physical assets are considered. Most importantly, once intangible capital is accounted for the role of (residual) total factor productivity becomes smaller.

1.2 Thesis contributions

In spite of the progress made over the last decade, much remains to be done to better understand the role of intangible capital in productivity and modern economic growth. This thesis seeks to contribute to this rapidly evolving field of research by providing four original studies that each take on a different aspect and focus of intangible capital.

(a) Knowledge spillovers from intangibles

Intangible assets are often non-rival and non-excludable, which open up the possibility of knowledge spillovers (Nakamura, 2010). In the case of R&D, this has long been known (Bloom, Schankerman & Van Reenen, 2013; Griliches, 1992). However, investment in R&D may not be the only source of knowledge spillovers between firms. Recent research has also shown knowledge spillovers from a broad set of non-R&D intangible assets using industry-level data (Goodridge, Haskel & Wallis, 2012a) or economy-wide data (Corrado, Haskel & Jona-Lasinio, 2014). Yet no study has focused on the potential spillovers from investment in organisation capital, the knowledge of management know-how and organisational structures at the firm level. This is despite the fact that the firm is the most appropriate unit for analysing spillovers, as estimation at the industry or economy-wide level cannot readily distinguish between productive benefits from own-firm investments and spillovers from investment in organisation capital by other firms. One example of such a spillover is Toyota's just-in-time production process that quickly spread to other car manufacturers (Liker & Morgan, 2006). Another example of the diffusion of management knowledge is the build-to-order (BTO) distribution system that originated with Dell Computers, but that has since been copied by firms in other industries, such as BMW (Gunasekaran & Ngai, 2005). Despite these promising cases, more comprehensive analysis on the potential spillover effects from investment in organisation capital had been lacking and Chapter 2 is the first to provide this.

Following the broader microeconomic literature (e.g. Eisfeldt & Papanikolaou, 2013), we use selling, general and administrative (SGA) expenses, an income statement item widely reported by U.S. firms, to proxy for organisation capital investment. We expect that firms are more likely to learn and benefit from the investments of firms that have similar technological characteristics, while firm profitability is likely to suffer from investments in organisation capital made by close competitors, i.e. firms that are selling in similar markets. We follow the methodology of Bloom, Schankerman and Van Reenen (2013) for the empirical analysis. Drawing on a large sample of company accounts data for 1,266 U.S. manufacturing firms over the period 1982-2011, we do not find evidence of knowledge spillovers from organisation capital that increase the productivity or market valuation of technologically similar firms. This lack of evidence stands in contrast to recent studies by Goodridge et al. (2012a) and Corrado et al. (2014) that do find positive productivity spillovers from broader measures of non-R&D intangible capital using more aggregate data. Given these differences, we argue that knowledge spillovers seem more likely to stem from intangible assets other than organisation capital and future research should look into these assets as a source of spillovers.

(b) Complementarity between intangibles and ICT

The complementary nature of intangible assets to ICT investment is well-established in microeconomic studies for U.S. firms (e.g. Bloom et al., 2012). However, little is known whether this relationship can be generalised to the macroeconomic level as comparable information on intangible investment at the level of industries for a set of countries had long been lacking. This question is not only interesting in its own right, but it could also be important to better understand why Europe has shown slower productivity growth than the U.S. since the mid-1990s. Prior studies by Basu et al. (2004) and Corrado et al. (2014) are two initial attempts at providing corroborating macroeconomic evidence. We further contribute to the literature by exploiting a newly developed intangible investment data at the industry-level, which provides a useful source of variation that could help to pin down the complementary relationship between intangibles and ICT.

More specially, we explore the complementary nature of intangibles in Chapter 3 by examining whether an increase in intangible capital deepening increases productivity more strongly in ICT-intensive industries relative to those that use little ICT. Methodologically, this analysis is based on the difference-in-differences approach developed by Rajan and Zingales (1998) and we use the industry-level intangible investment data constructed by Niebel, O'Mahony and Saam (2013) for a set of ten European countries and eleven industries over the period 1995-2007. The results show that the output elasticity of intangible capital is significantly larger for more ICT-intensive industries. By further distinguishing between different intangible asset types, we also show that only R&D and organisation capital exhibit a higher output elasticity in ICT-intensive industries, conforming to much of the evidence found in prior firm-level analyses. (Brynjolfsson & Hitt, 2003; Polder, van Leeuwen, Mohnen & Raymond, 2010).

(c) Intangibles in accounting for income differences

Most of the literature has found that differences in traditional factor inputs – labour and tangible capital – account for only a limited share of cross-country income differences (e.g. Caselli, 2005; Easterly & Levine, 2001; Hsieh & Klenow, 2010; Hall & Jones, 1999). However, the potential importance of differences in investment in intangible assets remains unexplored. It seems plausible that richer countries invest more intensively in intangible assets, thereby accounting for part of cross-country income variation. This possibility has not yet been examined as information on investment in intangibles is not available for a broad cross-section of countries and existing research has, instead, primarily focused on the role of intangible assets in accounting for a country's growth over time (Corrado et al., 2009; Fukao et al., 2009). Chapter 4 remedies this shortcoming by developing a large-scale macroeconomic data set on investment in intangible assets and uses the resulting data to analyse investment patterns across countries and incorporates intangible assets as an additional input in a development accounting exercise.

Our newly developed intangible investment database is consistent and internationally comparable for a set of 60 economies. With this new database we show that the share of investment in intangibles in GDP has been rising between 1995 and 2011 and there is a strong positive association between the level of economic development of a country and its investment intensity in intangibles. As a result, including intangible capital as an additional factor of production, we can account for substantially more of the variation in cross-country income levels than before. Depending on the assumptions regarding the output elasticities of factor inputs, the observed differences in intangible capital can account for up to 16 percentage points more of the cross-country income variation. This finding echoes with the preceding studies that find intangible capital to be important for a country's growth over time (Corrado et al., 2009; Fukao et al., 2009). In both cases, the role of (residual) productivity is smaller once intangible capital is taken into account.

(d) IPR protection and knowledge-intensive imports

Advanced technologies or knowledge in general can be embodied in goods and, through trade, diffuse across national borders (Keller, 2004). Countries with a slow pace of investment in intangible assets may find it desirable to import knowledge-intensive goods from abroad in order to enhance growth. But how can countries attract goods that have a large scope for knowledge diffusion? This is the topic of the last chapter of this thesis and we draw on the literature on the relationship between trade and intellectual property rights (IPR) protection to address this question.

Specifically, in Chapter 5, we examine whether more stringent IPR protection stimulates imports of goods with greater technology content. We proxy for the technology content of an imported product by the extent to which the originating industry invests in R&D. Then we follow the broader literature to measure the strength of a country's IPR protection using the index scores constructed by Ginarte and Park (1997). To establish the differential effects of IPR protection across product categories with varying degrees of technology intensity, we again apply the difference-in-differences approach as in Chapter 3. Using imports data for a sample of 119 countries over the period 1976-2010, we show that the impact of IPR protection on manufacturing imports is significantly stronger for products with greater technology content. More specifically, an increase in the level of IPR protection can lead to 22 percent faster increase in the value of imports of products at the 90th percentile of R&D intensity than for products at the 10th percentile.

Taken together, the chapters in this thesis cover a wide set of research questions on the relationship between intangible investments and economic growth. We summarise this in Table 1.1, which serves as a guidance to the remainder of this thesis.

Table 1.1: Overview of the Chapters

	Main research question	**Type of intangible asset studied**	**Data coverage**
Chapter 2	Does organisation capital lead to productivity spillovers?	Organisation capital	U.S. firms
Chapter 3	Are intangibles more productive in ICT-intensive industries?	All intangibles	Industries in the EU.
Chapter 4	How much more income variation across countries can be accounted for by intangible capital?	BE, OC, and R&D	60 economies
Chapter 5	Does stronger IPR protection lead to more knowledge-intensive imports?	R&D	119 countries

Notes: BE: brand equity, OC: organisation capital, R&D: research and development, IPR: intellectual property rights.

CHAPTER 2

Productivity spillovers of organisation capital*

2

2.1 Introduction

The role of knowledge-based assets for growth in advanced economies has drawn much recent interest from researchers and policy makers alike – see e.g. Corrado and Hulten (2010) and OECD (2013b). But while researchers are rapidly incorporating such assets into a standard 'sources-of-growth' framework (e.g. Corrado et al., 2009, 2012), much is yet unknown about the productive impact of such assets. Knowledge-based assets are typically intangible and thus non-rival and non-excludable. This opens up the possibility of knowledge spillovers (Nakamura, 2010). In the case of research and development (R&D) spending, this has long been known (e.g. Griliches, 1979, 1992) and recent firm-level evidence confirms the presence of R&D knowledge spillovers, see Bloom, Schankerman and Van Reenen (2013, BSV henceforth). But recent research has also shown knowledge spillovers from other knowledge-based assets, using industry-level data (Goodridge et al., 2012a, GHW henceforth), and economy-wide data (Corrado et al., 2014, CHJ henceforth).

In this chapter, we are the first to test for the effects of knowledge spillovers from organisation capital using firm-level data, rather than the more aggregated data that have been used so far.[1] Organisation capital can be thought of as the information a firm has about its assets and how these can be used in production (Prescott & Visscher, 1980). More specifically, it can be thought of as the value of brand names and knowledge

*This chapter is based on Chen and Inklaar (2016).

[1] The literature on productivity spillovers from foreign direct investment (FDI) – e.g. Liu (2006) and Keller and Yeaple (2009) – is partly related since domestic firms could learn from the foreign multinational's superior organisation. However, any learning taking place could also be on aspects of the multinational's productivity that are unrelated to organisation capital.

embedded in firm-specific resources (Corrado et al., 2005).[2] Several studies have shown organisation capital to be important for firm productivity[3] and it also seems important for explaining stock market returns across firms (Eisfeldt & Papanikolaou, 2013). Since knowledge of, for instance, organisational structures is non-rival and non-excludable, knowledge spillovers *between* firms could, in principle, also be important.

Relying on firm-level analysis to identify the effects of knowledge spillovers has clear advantages over analysis based on more aggregate data. Most importantly, we can distinguish between the productivity effects of own-firm investments and knowledge spillovers between firms, while analysis of aggregate data does not allow for such a clear distinction. Another advantage is the greater number of observations, which allows for more stringent testing. There are also downsides to firm-level analysis, including a less precise delineation of what constitutes investment in organisation capital. As we will argue later, though, the advantages outweigh the downsides.

In our analysis, we test whether firm productivity and market valuation are affected by the organisation capital stocks of similar firms, defining 'similar' in the same way as BSV. Since organisation capital relates to how production in a firm is organised, we expect that firms are more likely to learn and benefit from the investments of firms that are close in technology space. Firm profitability is likely to suffer, though, from investments in organisation capital made by close competitors, i.e. firms that are close in product market space. By locating firms in these two spaces, we can distinguish between the two types of spillovers and provide estimates of the marginal private and social returns to organisation capital investment.

We analyse a sample of 1,266 U.S. manufacturing firms over the period 1982-2011. We measure investment in organisation capital as selling, general and administrative (SGA) expenses, an approach followed by many in the firm-level analysis of organisation capital.[4] Past investments are cumulated into a stock of organisation capital and added to a production function along with (tangible) capital and labour. The proximity of firms in technology space is determined using patent data – an approach pioneered by Jaffe (1986) in the context of R&D knowledge spillovers. We assume that firms with patents in similar technology fields have greater potential to learn from each other's organisation capital. One example of such a spillover is Toyota's just-in-time system that quickly spread to other car manufacturers (Liker & Morgan, 2006). An example of

[2]See also Atkeson and Kehoe (2005). Conceptualising organisation capital as *embedded* in the organisation distinguishes it from measures of human capital, see e.g. Jovanovic (1979), Becker (1993).
[3]See e.g. Tronconi and Vittucci Marzetti (2011), Hulten and Hao (2008), Lev and Radhakrishnan (2005).
[4]See e.g. Eisfeldt and Papanikolaou (2013), Tronconi and Vittucci Marzetti (2011), Hulten and Hao (2008).

cross-industry diffusion is the build-to-order (BTO) distribution system that originated with Dell Computers, but that has since been copied by firms in other industries, such as BMW (Gunasekaran & Ngai, 2005). Though patents may not perfectly reflect the scope for such copying, they may be useful in identifying the technological position of the firm in a broad sense.[5]

Proximity in product market space is determined using the set of industries each firm is active in, assuming that greater overlap makes for fiercer competitors. Increased investment in organisation capital by competitors is likely to hurt firm performance: competitors may have to devote resources to copying successful business models such as the BTO system. Investment in organisation capital also includes spending on marketing and sales, and while some of this spending may expand the market, another part is aimed at capturing market share from competitors.[6]

Our findings are, first, that organisation capital contributes substantially to the firm's own productivity and market value and second, that investment in organisation capital by firms that are close in technology space has no effect on firm productivity or market valuation. In contrast, we find results similar to BSV for R&D knowledge and market-rival effects. Following the approach of BSV, we find that the marginal private return to organisation capital investments is positive, regardless of the chosen specification. The magnitude of the marginal social return is much more uncertain and could even be negative. Our results for organisation capital are robust across industries and to alternative distance measures and assumptions regarding the capitalisation of organisation capital. We argue that these results make it unlikely that organisation capital is the source of the knowledge spillovers found by CHJ and GHW. In the remainder of this chapter we outline the methodology and data (Section 2.2), present the results (Section 2.3) and conclude (Section 2.4).

2.2 Methodology and data

In this section we discuss the econometric approach to analysing organisation capital spillovers, followed by a description of the data and the methods used to construct the measures of organisation capital and the spillover pools.

[5]In addition, some business methods can be and have been patented since the 1990s, see Hall (2009).
[6]See Landes and Rosenfield (1994) on the long-lived nature of (some) advertising spending and, more broadly, Bagwell (2007) on the economics of advertising.

2.2.1 Econometric specification

We analyse two firm-level outcome variables, namely productivity and stock market valuation. In order to establish the effect of organisation capital and knowledge spillovers and market-rivalry effects on productivity, we estimate a production function; to establish the effects on market value, we estimate a market value equation.

Production function equation

To estimate the effect of organisation capital on firm productivity, we start from a production function for firm i at time t, extended to include organisation and R&D capital:

$$Y_{it} = A_{it}\ L_{it}^{\alpha}\ K_{it}^{\beta}\ G_{it}^{\gamma_1}\ R_{it}^{\gamma_2} \tag{2.1}$$

where Y is a measure of output, A is Hicks-neutral technology, K is physical capital, L denotes labour input, G is the stock of organisation capital and R is the stock of R&D capital. To determine the role of knowledge spillovers and any effects from product-market rivals, we log-differentiate equation (2.1) and estimate the following equation:

$$\begin{aligned} lnY_{it} = \gamma_1 lnG_{it} + \gamma_2 lnR_{it} + \varphi_1 lnKH_{it}^{G} + \varphi_2 lnMKT_{it}^{G} + \varphi_3 lnKH_{it}^{R} \\ + \varphi_4 lnMKT_{it}^{R} + w\mathbf{X}'_{it} + \eta_i + \tau_t + \epsilon_{it} \end{aligned} \tag{2.2}$$

Here KH_{it} capture knowledge spillovers from organisation capital or R&D capital (distinguished by the superscripts G and R) and MKT_{it} denotes any market-rival effect of organisation and R&D capital. This means that the technology term from equation (2.1), A, captures the effect from knowledge and market-rival spillovers; we further decompose technology into a correlated firm fixed effect (η_i), a full set of time dummies (τ_t), and an idiosyncratic component (ϵ_{it}) that is allowed to be heteroskedastic and serially correlated. Physical capital K and labour input L are combined into $\mathbf{X}'$. Note that we do not include a measure of material inputs, since fewer firms report on this item, thus reducing the sample size notably. However, we show in Appendix Table 2.11 that the main production function results are robust to whether materials are included or not.

Our main parameter of interest in this equation is φ_1, which captures knowledge spillovers from organisation capital. Based on the R&D spillover literature, we expect φ_3 to be significantly positive. BSV argue, based on the industrial organisation literature, that φ_2 and φ_4 should be zero: organisation or R&D capital of product-market rivals may hurt profitability due to loss of market share, but standard theories do not predict an effect on productivity.

The estimation of equation (2.2) can be affected by measurement error and simultaneity bias. Measurement error arises because firm sales are not deflated by a firm-level price index, but by an industry-level price index obtained from the Bureau of Economic Analysis (BEA). When prices vary across firms within an industry, part of the variation in sales is due to variation in prices rather than quantities (Foster, Haltiwanger & Syverson, 2008). To deal with this problem, we include the industry output index and price index as part of the control variables $\mathbf{X}'$, following the arguments of Klette and Griliches (1996) and De Loecker (2011). Simultaneity bias causes concern because there might be unobserved productivity shocks that are known to the firms when they choose their input levels (Griliches & Mairesse, 1998). The error term is assumed to include a firm fixed effect (η_i), because if the deviation between firm and industry prices is largely time-invariant, this should go a long way towards dealing with the problem of firm-specific prices. Moreover, to the extent that unobserved, firm-specific productivity is also time-invariant, the simultaneity problem should also be controlled for. As these assumptions might not hold in practice, we also consider a GMM specification, where lagged values of the explanatory variables are included as instruments.[7]

Market value equation

In estimating the effect of organisation capital on firm market value, we also follow the approach outlined in BSV, but extended to include organisation capital as another factor influencing firm market value as well as a possible source of spillovers. BSV, in turn, build on the work of Griliches (1981) in formulating their market value equation. Tobin's Q, the firm's market value over the book value of assets is used as the dependent variable and explained by organisation and R&D capital, and spillover terms:

$$\begin{aligned} ln\left(\frac{V}{A}\right)_{it} &= ln\left(1+\psi_1\left(\frac{G}{A}\right)_{it}\right) + ln\left(1+\psi_2\left(\frac{R}{A}\right)_{it}\right) + \lambda_1 lnKH^G_{it} \\ &\quad + \lambda_2 lnMKT^G_{it} + \lambda_3 lnKH^R_{it} + \lambda_4 lnMKT^R_{it} + w\mathbf{X}' + \eta_i + \tau_t + \epsilon_{it} \end{aligned} \tag{2.3}$$

where V is the market capitalisation of the firm (the value of common and preferred stock and total net debt) and A is the book value of its assets – including net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and

[7] But note that given our long time period, with approximately 16 years of a data for the average firm, the bias of the OLS fixed effects estimator on the variables that are not strictly exogenous but only weakly exogenous is likely to be small.

capitalised intangibles, but excluding the (estimated) value of organisation and R&D capital. Note that $ln\left(1+\psi_1\left(\frac{G}{A}\right)_{it}\right)$ is a non-linear term and that both $\left(\frac{G}{A}\right)_{it}$ and $\left(\frac{R}{A}\right)_{it}$ are typically not small. A first-order approximation would thus not be accurate, so we use a higher-order expansion instead. As in the production function estimation, any knowledge spillovers from organisation capital (λ_1) and from R&D capital (λ_3) should have a positive impact on Tobin's Q. Unlike productivity, Tobin's Q would be affected if successful innovations from R&D and organisation capital of competitors were to reduce the firm's market share. The market-rival effects, λ_2 and λ_4, would thus be negative.

Data sources

We obtained company accounts and stock market data from Datastream and matched these to patent data from Bureau van Dijk's Orbis database. We solely focus on manufacturing firms as these are the most intensive investors in intangible assets (Goodridge, Haskel & Wallis, 2012b).

For this reason, we also restrict our sample to manufacturing firms with at least one patent. This leads to data on the patenting activity of 1,722 U.S. manufacturing firms, obtained from Orbis. These patent data are matched to company accounts data from Datastream using firm international securities identification number (ISIN) codes as the unique firm identifier. From Datastream we collect information on the number of employees (WC07011), total sales (WC01001), the stock of physical capital (net property, plant, and equipment, WC02501), investment in organisation capital (selling, general and administrative expenses, WC01101), R&D expenditure (WC01201), the market value of the company (MVC), preferred stock (WC03451), current assets (WC02201), total debt (WC03255), total inventories (WC02101) and total intangibles (WC02649) all for the period 1982–2011. Of the 1,722 patenting firms from Orbis, 212 were not covered in Datastream and a further 244 firms had missing values for one or more of the company accounts data items. Dropping these firms results in an unbalanced panel of 1,266 U.S. manufacturing firms with over 18,000 usable observations. Table 2.1 provides some basic descriptive statistics on the key variables.

The table shows that the sample covers mostly larger firms and, since the means exceed the medians, the size distribution is skewed. Furthermore, we can follow the firms in our sample for a sizeable number of years, as indicated by the 'Av. years' column. The (internal) stocks of organisation capital and R&D capital (see Section 2.3 for measurement details) are large compared to the stock of physical capital, which suggests that these knowledge-based assets could be important for productivity. The potential to learn from organisation capital and R&D capital investments by firms that are close in technology space (Section 2.4) is large, as indicated by the size of the external stocks. The external stocks of market rivals (Section 2.5) are comparatively smaller.

Table 2.1: DESCRIPTIVE STATISTICS

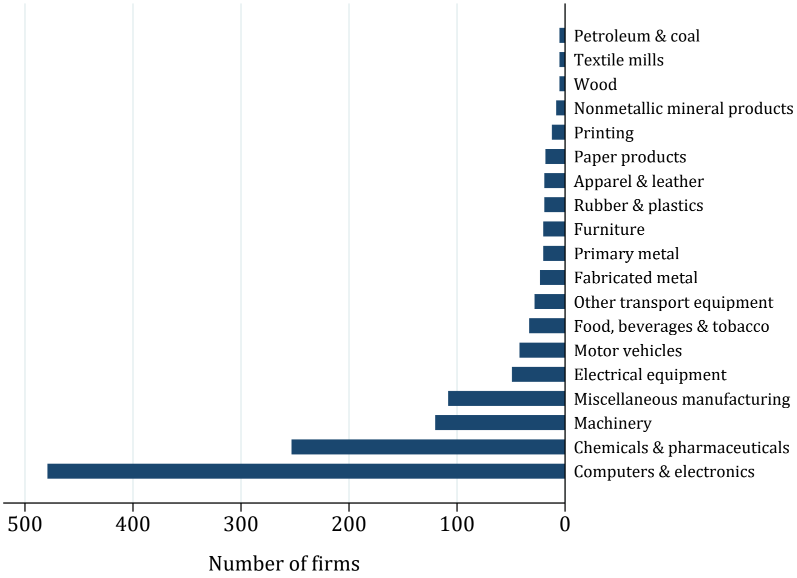
	Median	Mean	SD	Btw. SD	Wit. SD	Av.years	N
Sales	136	2,636	14,087	10,362	4,672	17.8	22,587
Market value	230	3,774	17,654	10,729	10,780	16.4	20,731
SGA expenses	32	404	1,431	1,016	628	15.7	18,695
R&D expenses	10	120	504	323	259	15.8	18,758
Physical capital	31	802	4,798	3,444	1,768	17.6	22,227
Employees	885	9,096	26,407	19,422	9,328	17.0	21,544
Internal OC	108	1,435	5,084	3,687	2,049	15.8	18,606
External OC (tech space)	28,605	32,710	21,669	14,589	16,028	30.0	37,980
External OC (market space)	1,852	3,156	3,762	2,963	2,320	30.0	37,980
Internal RD	49	609	2,606	1,676	1,318	15.8	18,678
External RD (tech space)	11,203	14,628	11,259	6,471	9,215	30.0	37,980
External RD (market space)	832	1,727	2,435	1,634	1,805	30.0	37,980
Technological fields	29	62.75	88.85	n.a.	n.a.	n.a.	1,266
Product markets	3	3.01	1.86	n.a.	n.a.	n.a.	1,266

Notes: 'Btw. SD' illustrates the variation between firms (averaged over time), while 'Wit. SD' illustrates the variation over time, ignoring the between-firm variation. 'N' is the number of observations and 'Av. years' indicates the average number of years for which firms are in the dataset. Sales are deflated by the industry price index and SGA expenses are deflated by the implicit GDP price deflator; all price indices are from the Bureau of Economic Analysis. Employees, technology fields and product markets are in numbers; all other variables are in millions of 2005 U.S. dollars. Computation of the external OC stocks, R&D stocks, technological fields and number of markets is explained in Sections 2.3–2.5

By restricting our sample to firms holding at least one patent, our sample consists of relatively large firms: the median number of employees in Table 2.1 is 885 versus 581 for a sample that also includes non-patenting firms (see Appendix Table 2.8). However, as shown in Appendix Table 2.9, the production function estimates (without spillover terms) are comparable to results based on our more restricted sample, suggesting limited scope for sample selection bias.

Figure 2.1 shows the distribution of firms across 19 broader (2-digit) manufacturing industries. The sample of firms is fairly concentrated in the more high-tech sectors of the economy, such as computers & electronics and chemicals & pharmaceuticals, with the top-five industries accounting for around 80% of the firms. As shown in Appendix Table 2.10, our results are not influenced by any of these well-represented industries.

Figure 2.1: Distribution of Firms across Industries



2.2.2 Measuring organisation capital

Investment in organisation capital has been measured in a number of ways in the literature. These include business surveys (Black & Lynch, 2005), part of the wage bill of managers (Squicciarini & Le Mouel, 2012), the residual from a production function (Lev & Radhakrishnan, 2005) and selling, general and administrative (SGA) expenses (Tronconi & Vittucci Marzetti, 2011; Eisfeldt & Papanikolaou, 2013). Given data availability, we opt to use SGA expenses for measuring investment in organisation capital. Note that SGA expenses covers many different types of expenditures, and these are typically not broken down in great detail. One of the major items would be advertising expenditure, which represents 9% of SGA expenses for firms which separately distinguish this item.

Lev and Radhakrishnan (2005) present detailed arguments and examples of how resources allocated to this expense item can yield improvements in employee incentives, distribution systems, marketing technologies, and a wide range of other organisational structures. Further evidence is from Eisfeldt and Papanikolaou (2013) who find that their measure of organisation capital based on SGA expenses correlates highly with the managerial quality scores constructed by Bloom and Van Reenen (2007). This evidence suggests that using SGA expenses to measure organisation capital is informative of the quality of management practices across firms.

SGA expenses includes R&D expenditure,[8] so to focus on organisation capital we subtract R&D expenditure to get our measure of investment in organisation capital.[9] To convert this investment flow into an organisation capital stock, we apply the perpetual inventory method:

$$G_{i,t} = (1 - \delta) \cdot G_{i,t-1} + \frac{SGA_{i,t}}{p_t} \tag{2.4}$$

where p_t is the implicit GDP deflator from the Bureau of Economic Analysis. To implement the law of motion in equation (2.4), an initial stock and a rate of depreciation must be chosen. Assuming a steady-state relationship from the Solow growth model, the initial stock can be calculated according to:

$$G_0 = \frac{SGA_0}{g + \delta} \tag{2.5}$$

where g denotes the steady-state growth rate of organisation capital and δ is the rate at which organisation capital become obsolete. According to the aggregate estimates of the INTAN-Invest database compiled by Corrado et al. (2012), organisation capital grows at an average rate of 6% per year, so we use this value for g in equation (2.5).

Organisation capital can depreciate over time for a variety of reasons. The existing management practices become obsolete if improvements come along. Organisation capital can also erode through work attrition and the adoption of new products or production processes (Hulten & Hao, 2008). In the existing empirical works, the assumed rate of depreciation various between 10% (Tronconi & Vittucci Marzetti, 2011) and 40% (Corrado et al., 2009). Given that organisation capital has two contrasting components: a long-lasting learning-by-doing element which depreciates like R&D; and a short-lived organisational 'forgetting' dynamic which depreciates like advertising, a rate in the middle of the range is chosen as our baseline rate; that is, $\delta = 0.25$. The alternative rates of 10% and 40% will be considered in the robustness analysis. R&D capital is estimated in a similar fashion as organisation capital; following BSV, we use a depreciation rate of 15%.

2.2.3 Technological proximity

We assume that firms are more likely to learn from the organisation capital of firms that are technologically similar. Moreover, we assume that a firm's patent portfolio defines

[8]At least, according to the definitions employed by Datastream and Compustat.

[9]Tronconi and Vittucci Marzetti (2011) measure investment as 20% of this amount to reflect that not all SGA expenses add to organisation capital. This is irrelevant from an econometric point of view.

its technological position and that firms developing or utilising similar technologies have organised their organisations similarly. As discussed earlier, the diffusion of just-in-time production system and build-to-order supply chain management are two cases in point.

We use the patent data provided in Orbis, which is based on the European Patent Office's PATSTAT database. This database covers over 80% of the world's patents to date and these patents are classified by four-digit international patent classification (IPC) code. This means that even if the firm had been awarded patents from patenting offices in different countries, their patents can be compared. Our sample of 1,266 manufacturing firms obtained around half a million patents spanning 612 technology fields, as defined by the first three digits of the IPC code.[10] All patents of a firm are included because it is not possible to select patents for a specific time frame, but this is also a helpful feature, as it defines the 'average' technological position of a firm, rather than focusing only on activity for a specific period.

Define the vector $T_i = (T_{i1}, T_{i2}, T_{i3}..., T_{i612})$, where $T_{i\tau}$ indicates the number of patents of firm i in technology class τ. The technological proximity between any firm i and j is then defined as the uncentred correlation of patent portfolios, as in Jaffe (1986):

$$P_{i,j}^{KH} = T_i T_j' / \left(T_i T_i'\right)^{\frac{1}{2}} \left(T_j T_j'\right)^{\frac{1}{2}} \tag{2.6}$$

The larger the proximity the more effective knowledge of organisation capital can diffuse between firms i and j (or vice versa). As indicated in Table 2.1, the median firm is active in 29 technological fields, providing ample opportunity for learning from other firms in any of these fields. Analogous to BSV, the spillover pool of management know-how available to firm i at time t is calculated as:

$$KH_{i,t} = \sum_{j,j \neq i} P_{i,j}^{KH} \times G_{j,t} \tag{2.7}$$

2.2.4 Product market proximity

We also locate firms in product market space, using information on the industries in which firms are active. Datastream provides up to eight industry codes for each firm at the four-digit standard industrial classification (SIC) level, which means that a firm can be active in up to eight different markets. As shown in Table 2.1, firms on average report sales activities in 3 different markets out of a total of 569 different four-digit SIC

[10] The level of disaggregation of a 3-digit IPC code generates a workable and comparable amount of technology classes to that of BSV. A further breakdown of the classification codes to the fourth digit is not pursued as Henderson, Jaffe and Trajtenberg (2005) argue that a finer disaggregation would be subject to a greater degree of measurement error.

industries.[11] Define the vector $S_i = (S_{i1}, S_{i2}, S_{i3}..., S_{i569})$, where S_{ik} indicates whether or not firm i is active in market k. In contrast to BSV, we have no information on the share of sales in each market, but that information was not crucial to their results.[12] Analogous to the technology proximity measure, the market proximity measure for any two firms i and j is calculated as:

$$P_{i,j}^{MKT} = S_i S_j' / \left(S_i S_i'\right)^{\frac{1}{2}} \left(S_j S_j'\right)^{\frac{1}{2}} \tag{2.8}$$

The spillover pool of product market for firm i in year t is then constructed as:

$$MKT_{i,t} = \sum_{j,j \neq i} P_{i,j}^{MKT} \times G_{j,t} \tag{2.9}$$

For the separate identification of knowledge and market rival spillovers we rely on differences in the two proximity measures. The correlation between the proximity metrics in technology and product-market space is 0.196, indicating substantial variation between the two proximity measures.

To illustrate how firms can be located differently in technology and market space, consider the case of Apple, Intel and Dell. These three firms are all close in technology space, with $\mathrm{P}^{\mathrm{KH}}_{\mathrm{Apple,Intel}} = 0.93$, $\mathrm{P}^{\mathrm{KH}}_{\mathrm{Apple,Dell}} = 0.87$ and $\mathrm{P}^{\mathrm{KH}}_{\mathrm{Dell,Intel}} = 0.84$. These proximity measures are high relative to the average $\mathrm{P}^{\mathrm{KH}}_{\mathrm{i,j}}$ of 0.28. However, Apple and Dell are both active in the product market for computers (with Apple also active in other markets) leading to $\mathrm{P}^{\mathrm{MKT}}_{\mathrm{Apple,Dell}} = 0.37$. In contrast, Apple and Dell do not share any product market with Intel, so that $\mathrm{P}^{\mathrm{MKT}}_{\mathrm{Apple,Intel}} = \mathrm{P}^{\mathrm{MKT}}_{\mathrm{Dell,Intel}} = 0$.

2.3 Results

In this section we discuss the main empirical findings, with first results of production function estimates without spillovers, followed by the evidence on the presence of spillovers for productivity and market valuation, including the robustness of that evidence. Finally, we discuss what the spillover results imply in terms of the private and social returns to investment in organisation capital and discuss our results in relation to GHW and CHJ.

[11]Only few firms (5%) are active in eight different markets, while many more firms (29%) are active in just two markets.

[12]For a further comparison, we constructed a market spillover variable for R&D stock like the one used by BSV but based on our information on the number of active markets. For 237 firms, this market spillover variable can be compared to the corresponding BSV variable. The correlation coefficient is high at 0.68, giving confidence that our market spillover measure is comparable to theirs.

2.3.1 Production function estimates without spillovers

Table 2.2 shows production function estimates with firm and year fixed effects and OLS estimation (FE) or generalised method of moments estimation (GMM). In the GMM estimates, we follow Tronconi and Vittucci Marzetti (2011) and use lagged values of the inputs as instruments; specifically, we use X_{it-2} and X_{it-3} as instruments for X_{it}. The first two columns of Table 2.2 show production function results with only capital and labour as inputs. Both are highly significant but the sum of the coefficients is significantly smaller than one, indicating decreasing returns to scale. In the next two columns, the stock of organisation capital is added to the production function and it enters with a highly significant coefficient. This finding is in line with the earlier firm-level analyses of organisation capital and provides further support for considering intangible assets as factors in production alongside tangible capital (Corrado et al., 2005, 2009; Van Ark, Hao, Corrado & Hulten, 2009).

The output elasticity of organisation capital is substantial in size, between 0.222 and 0.469, a similar range as found by Tronconi and Vittucci Marzetti (2011) for their sample of European firms. In columns (5) and (6), we include R&D capital, but exclude organisation capital, while in columns (7) and (8), both sets of capital are included. By itself, the R&D capital output elasticity is positive and, in the case of the FE specification, significantly so. The elasticity turns negative when R&D and organisation capital are included jointly, but as shown in Appendix Table 2.9, this negative coefficient is not robust to the set of firms that is included. With these results, a necessary condition for there to be any scope for knowledge spillovers from organisation capital has been satisfied: organisation capital contributes systematically to own-firm productivity. What is further notable is that the GMM specifications with organisation capital show constant returns to scale. This is in contrast with the results of CHJ, whose findings suggest increasing returns to scale. We discuss our findings in relation to theirs in more detail below.

2.3.2 Spillovers to productivity and market values

Table 2.3 presents the main productivity spillover results. The first two columns show the results with only spillover terms related to organisation capital; columns (3) and (4) mimic the BSV specification about R&D spillovers; and columns (5) and (6) include both sets of spillover variables. The main result is that there is no robust evidence of OC knowledge spillovers on productivity. When also allowing for R&D knowledge spillovers, the point estimates for OC knowledge spillover even turn negative in column (6), but

Table 2.2: Firm Production Function Estimates with Organisation Capital

	(1) FE	(2) GMM	(3) FE	(4) GMM	(5) FE	(6) GMM	(7) FE	(8) GMM
Physical capital (K)	0.178***	0.151***	0.140***	0.199***	0.182***	0.183***	0.148***	0.191***
	(0.020)	(0.038)	(0.021)	(0.043)	(0.021)	(0.043)	(0.020)	(0.042)
Employees (L)	0.712***	0.786***	0.490***	0.581***	0.662***	0.738***	0.495***	0.587***
	(0.029)	(0.050)	(0.035)	(0.067)	(0.035)	(0.061)	(0.035)	(0.067)
Organisation capital (G)			0.469***	0.222***			0.556***	0.289***
			(0.035)	(0.047)			(0.043)	(0.057)
R&D capital (R)					0.117***	0.043	-0.123***	-0.076**
					(0.027)	(0.032)	(0.032)	(0.038)
Number of observations	20,516	16,970	17,103	13,593	17,169	13,658	17,103	13,593
Number of firms	1,238	1,200	1,149	1,077	1,150	1,078	1,149	1,077
R^2	0.704	0.700	0.748	0.749	0.728	0.736	0.750	0.750
Returns to scale (H^0: RTS=1)	0.890***	0.937**	1.099***	1.001	0.962*	0.965	1.075***	0.990
Hansen J p value		0.313		0.127		0.505		0.234
Weak instrument		118.1		52.33		63.70		39.26

Notes: FE: OLS with firm fixed effects; GMM: based on the two-step efficient generalised method of moments (GMM) estimator, using X_{it-2} and X_{it-3} as instruments for X_{it}. Dependent variable in all specifications is real sales and all specifications include firm and year fixed effects, the industry output index and the lag of the industry output index and the industry price index. Robust standard errors, clustered by firm, are shown in parentheses. Returns to scale tests whether the sum of all inputs (K, L and G and R were included) is significantly different from one. The Hansen J p value is based on a test of overidentifying restrictions, where the null hypothesis is that the instruments are valid. The Weak instrument line gives the Wald F-statistic of the first-stage regression. If this statistic exceeds 11–12 (depending on the specification), the IV bias is less than 5% of the bias of using OLS, see Stock and Yogo (2005). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

remain insignificant. In contrast, the R&D knowledge spillover term is significantly positive by itself, in columns (3) and (4). The R&D knowledge spillover term turns insignificant in columns (5) and (6) mostly because the OC and R&D knowledge spillover terms are highly correlated. Another factor is that our use of robust standard errors, clustered by firm, turns out be a more conservative approach than the Newey-West HAC standard errors used by BSV.[13]

Table 2.3: Organisation Capital Spillovers to Firm Productivity

	(1) FE	(2) GMM	(3) FE	(4) GMM	(5) FE	(6) GMM
OC knowledge spillovers	0.497*	0.323			0.149	–0.157
	(0.254)	(0.264)			(0.381)	(0.433)
OC market rivals	–0.157***	–0.273***			–.188***	–0.326***
	(0.051)	(0.087)			(0.060)	(0.092)
RD knowledge spillovers			0.468**	0.342*	0.353	0.380
			(0.200)	(0.183)	(0.298)	(0.323)
RD market rivals			–0.044	–0.061	0.040	0.064
			(0.040)	(0.047)	(0.051)	(0.058)
Physical capital (K)	0.148***	0.194***	0.148***	0.191***	0.148***	0.197***
	(0.020)	(0.042)	(0.020)	(0.042)	(0.020)	(0.042)
Employees (L)	0.492***	0.572***	0.494***	0.586***	0.493***	0.576***
	(0.035)	(0.067)	(0.035)	(0.067)	(0.035)	(0.067)
Organisation capital (G)	0.563***	0.308***	0.555***	0.284***	0.565***	0.311***
	(0.043)	(0.058)	(0.043)	(0.057)	(0.043)	(0.059)
R&D capital (R)	–0.125***	–0.077**	–0.124***	–0.072*	–0.132***	–0.089**
	(0.032)	(0.038)	(0.033)	(0.040)	(0.033)	(0.041)
Number of observations	17,103	13,593	17,103	13,593	17,103	13,593
Number of firms	1,149	1,077	1,149	1,077	1,149	1,077
R^2	0.750	0.751	0.750	0.750	0.750	0.751
Returns to scale (H^0: RTS=1)	1.077***	0.997	1.073***	0.989	1.074**	0.994
Hansen J p value		0.204		0.420		0.409
Weak instrument		32.23		26.76		24.23

Notes: The table shows the results from estimating equation (2.2). See notes to Table 2.2 for details of the production function estimation. The OC knowledge spillovers variable is based on equation (2.7) and the R&D knowledge spillovers variable is defined analogously. The OC market rivals variable is based on equation (2.9) and the R&D market rivals variable is defined analogously. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[13] We confirm this using the BSV data, with results shown in Appendix Table 2.12.

A striking result is the negative OC market rival effect. Taken at face value, this implies that productivity is hurt by rival firm investments in organisation capital. As mentioned before, such a 'face value' result is hard to reconcile with the industrial organisation literature, which considers only a negative market rival effect on firm profitability, not on productivity.[14] One explanation for the negative market rival effects could be that the inclusion of indexes of industry output and industry prices does not adequately correct for the lack of information on firm-level prices. The market structure in the model of De Loecker (2011) is one of monopolistic competition in a differentiated-product market, but between-firm competition could be fiercer. In that case, the negative coefficients on OC market rivals could reflect a profitability effect, rather than a productivity effect.

Another possibility is that adjustment costs lead to a short-term loss of efficiency as firms need to adjust their inputs to their reduced market share. Given these alternative explanations for the negative coefficients and the lack of a theory-consistent explanation that could help understand why firm productivity would be negatively affected, we do not take these results as serious evidence of negative productivity spillovers.

We now turn to estimating the market value equation (2.3). Table 2.4 shows the estimation results using either an OLS firm fixed-effect estimation (FE), or a specification where the spillover variables enter the equation with one lag (FE-Lag). We chose the FE-Lag approach rather than the GMM approach from the production function estimation because the test for overidentifying restrictions showed that lagged values of the explanatory variables were not valid instruments. We thus follow the estimation approach of BSV in using the spillover variables at $t-1$ rather than at t.

The table shows clear negative market rival effects from R&D, with the coefficients consistently significant and negative in columns (3)–(6). Columns (1) and (2) suggest similar market rival effects from organisation capital, but they are not robust to the inclusion of the R&D market rival effect. Similarly, the significantly negative knowledge spillover terms for organisation capital and R&D are not robust, as shown in column (5) and (6). It is notable that BSV find significantly positive R&D knowledge spillovers, while we do not. Further checks using the data and programme files provided by BSV suggest their R&D knowledge spillovers evidence is not fully robust. For one, their use of Newey-West HAC standard errors is less conservative than our use of robust standard errors, clustered by firm. Second, their data cover 1981–2001, but their estimation sample only uses data for the period 1985–2000. Appendix Table 2.12 shows that the evidence for R&D knowledge spillovers is less convincing when using the more conservative standard errors and the full sample period.

[14] See also Denicolò and Zanchettin (2014).

Table 2.4: Organisation Capital Spillovers to Firm Market Value

	(1) FE	(2) FE-Lag	(3) FE	(4) FE-Lag	(5) FE	(6) FE-Lag
OC knowledge spillovers	-1.529***	-1.764***			-0.934	-1.315
	(0.586)	(0.572)			(1.016)	(0.945)
OC market rivals	-0.207*	-0.254**			0.061	0.063
	(0.111)	(0.103)			(0.139)	(0.130)
RD knowledge spillovers			-1.048*	-1.152**	-0.459	-0.344
			(0.543)	(0.516)	(0.899)	(0.831)
RD market rivals			-0.308***	-0.336***	-0.336***	-0.367***
			(0.085)	(0.081)	(0.104)	(0.100)
OC capital/capital stock	0.328***	0.327***	0.296***	0.291***	0.295***	0.291***
	(0.050)	(0.050)	(0.052)	(0.052)	(0.052)	(0.052)
RD capital/capital stock	0.193***	0.196***	0.228***	0.234***	0.228***	0.234***
	(0.048)	(0.048)	(0.050)	(0.050)	(0.050)	(0.050)
Number of observations	14,931	14,931	14,931	14,931	14,931	14,931
Number of firms	1,043	1,043	1,043	1,043	1,043	1,043
R^2	0.302	0.303	0.304	0.306	0.305	0.306

Notes: FE: fixed effects; FE-Lag: fixed effects with the spillover variables lagged by one period. Dependent variable in all estimations is Tobin's Q, defined as the market value of equity plus debt, divided by the stock of fixed capital. A seventh-order polynomial in (OC stock/capital stock) and a fifth-order polynomial in (R&D stock/capital stock) are included, but only the first term is shown for brevity. All specifications include firm and year fixed effects. Robust standard errors, clustered by firm, are shown in parentheses. *** p<0.01, ** p<0.05, *p<0.1

2.3.3 Sensitivity analysis

In Tables 2.5 and 2.6, we present regression results that vary the measurement of proximity in technology and market space and of organisation capital. We first aim to test whether our results depend on the definition of proximity in the technology and product market space. In the baseline model, a firm's position in technology space is determined based on the 3-digit IPC classification of its patent portfolio and its position in market space is determined based on the 4-digit SIC industry codes the firm is active in. We consider two alternatives: (a) IPC code at 2-digit with SIC code at 3-digit denoted 'Proximity (2-3)' and (b) IPC code at 1-digit with SIC code at 2-digit denoted 'Proximity(1-2)'. For brevity, we only report the GMM specifications in Table 2.5, comparable to column (6) of Table 2.3; in Table 2.6 we only report the fixed effect lagged (FE-Lag) specifications, comparable to column (6) of Table 2.4. Results for the fixed effect specifications are available upon request. We also vary the assumed depreciation rate for organisation capital. The 25% depreciation of the baseline model is an average of commonly-used depreciation rates in the literature, but we also consider a much lower rate of 10% and a much higher rate of 40%.

Table 2.5: OC Spillovers to Firm Productivity – Sensitivity Analysis

	(1) Proximity (2–3)	(2) Proximity (1–2)	(3) $\delta = 10\%$	(4) $\delta = 40\%$
OC knowledge spillovers	0.323	–1.761	–0.162	–0.232
	(0.807)	(1.550)	(0.467)	(0.436)
OC market rivals	–0.165**	–0.580***	–0.196**	-0.258***
	(0.078)	(0.177)	(0.080)	(0.067)
RD knowledge spillovers	0.020	1.387*	0.239	0.446
	(0.491)	(0.733)	(0.322)	(0.325)
RD market rivals	0.027	0.109	0.018	0.040
	(0.066)	(0.097)	(0.060)	(0.052)
Physical capital (K)	0.195***	0.183***	0.212***	0.167***
	(0.042)	(0.042)	(0.043)	(0.042)
Employees (L)	0.590***	0.598***	0.644***	0.536***
	(0.066)	(0.066)	(0.066)	(0.066)
Organisation capital (G)	0.284***	0.298***	0.205***	0.356***
	(0.056)	(0.057)	(0.057)	(0.059)
R&D capital (R)	–0.076**	–0.091**	–0.048	–0.071*
	(0.038)	(0.039)	(0.043)	(0.037)
Number of observations	13,593	13,593	13,593	13,593
Number of firms	1,077	1,077	1,077	1,077
R^2	0.750	0.751	0.744	0.756
Returns to scale (H^0: RTS=1)	0.993	0.987	1.013	0.989
Hansen J p value	0.594	0.309	0.098	0.769
Weak instrument	20.66	26.14	21.40	21.59

Notes: See notes to Table 2.2 on the estimation of the production function and to Table 2.3 on the spillover terms. For brevity, only GMM specifications are shown, comparable to column (6) of Table 2.3 for the baseline model. In the baseline model, patents are categorised into 3-digit patent categories and 4-digit industry categories for determining proximity in technology space [equation (2.6)] and in market space [equation (2.8)]. Column 'Proximity (2–3)' uses 2-digit patent categories and 3-digit industry categories; column 'Proximity (1–2)' uses 1-digit patent categories and 2-digit industry categories. In the baseline model, organisation capital is assumed to depreciate at a geometric rate δ of 25%. The column '$\delta = 10\%$' assumes a 10% rate and the column '$\delta = 40\%$' assumes a 40% rate. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.6: OC Spillovers to Firm Market Value – Sensitivity Analysis

	(1) Proximity (2–3)	(2) Proximity (1–2)	(3) $\delta = 10\%$	(4) $\delta = 40\%$
OC knowledge spillovers	–1.168	2.077	–1.965*	–0.761
	(1.429)	(2.058)	(1.107)	(0.853)
OC market rivals	0.148	–0.257	0.047	0.109
	(0.150)	(0.241)	(0.146)	(0.122)
RD knowledge spillovers	–0.657	–1.954*	–0.241	–0.746
	(1.059)	(1.084)	(0.845)	(0.817)
RD market rivals	–0.335***	–0.222	0.400***	–0.421***
	(0.112)	(0.208)	(0.099)	(0.095)
OC capital/capital stock	0.307***	0.314***	0.263***	0.284***
	(0.051)	(0.051)	(0.042)	(0.041)
RD capital/capital stock	0.216***	0.206***	0.412***	0.424***
	(0.049)	(0.049)	(0.032)	(0.031)
Number of observations	14,931	14,931	14,931	14,931
Number of firms	1,043	1,043	1,043	1,043
R^2	0.304	0.301	0.307	0.306

Notes: See notes to Table 2.4 on the estimation of the market value equation and notes to Table 2.5 for an explanation of the column headings. For brevity, only the FE-Lag specifications are shown, comparable to column (6) of Table 2.4 for the baseline model. *** p<0.01, ** p<0.05, *p<0.1

The most important result from Table 2.5 and 2.6 is that there are no significant knowledge spillovers from organisation capital to productivity (Table 2.5) or market values (Table 2.6), regardless of the proximity definitions or the assumed depreciation rate. When assuming a lower depreciation rate, the output elasticity of organisation capital is smaller, because the stocks of organisation capital are larger. Despite this variation, the null hypothesis of constant returns to scale also cannot be rejected under the two alternative depreciation rates. Further sensitivity analysis is in Appendix Table 2.10, which shows that excluding a single industry at a time does not affect the results.

2.3.4 Private and social returns to organisation capital

With our results, we can gauge the marginal social and private returns to investment in organisation capital, again following BSV. Consider, first, the output elasticity $\gamma_1 = \rho \times (G/Y)$, where ρ is the marginal productivity of organisation capital G. If one assumes a constant marginal product γ_1 and a constant discount rate r along with an infinite planning horizon, then ρ can be given the economic interpretation of a marginal gross internal rate of return.[15] In BSV, the marginal social return (MSR) to organisation capital of firm i is defined as the increase in aggregate output generated by a marginal increase in firm i's organisation capital stock:

$$MSR = (Y/G) \cdot (\gamma_1 + \varphi_1) \tag{2.10}$$

where γ_1 and φ_1 are the coefficients from estimating equation (2.2) as given in Table 2.3. The MSR can be interpreted as the marginal product of a firm's organisation capital contributed: (1) directly from firm's own organisation capital stock γ_1 and (2) indirectly from the external stock of management knowledge, φ_1. The marginal private return (MPR) is defined as the increase in firm i's output generated by a marginal increase in its own stock of organisation capital:

$$MPR = (Y/G) \cdot (\gamma_1 - \sigma\lambda_2) \tag{2.11}$$

Own organisation capital increases a firm's own sales, thus γ_1 is part of the MPR. Also included is λ_2 since the firm's own organisation capital has a business-stealing effect on its product market rivals, as given in the market value equation. This business-stealing effect increases the private incentive to invest in organisation capital by redistributing output between firms. The business-stealing effect on market values will generally consist of a (negative) impact on rival firms' prices and output levels. The share of the overall effect that falls on output is represented by parameter σ and, in line with BSV, is set at $\frac{1}{2}$. More in general, the size of σ will depend on the precise model of product market competition.

As our estimates of the different parameters (γ_1, φ_1 and λ_2) vary notably between specifications and because the spillover parameters φ_1 and λ_2 are often not statistically significant, it is most helpful to report 95-percent confidence intervals (estimated using the delta method) alongside the point estimates. In Table 2.7, we report the MSR and MPR estimates based on parameters from two specifications, namely from column 2 of Tables 2.3 and 2.4 – which give relatively optimistic estimates of organisation capital knowledge spillovers – and column 6 of Tables 2.3 and 2.4 – which give relatively pessimistic estimates. As the table shows, the MPR of investment in organisation capital is significantly positive. Column 2 of Table 2.4 showed a significantly negative business-stealing effect, which results in a higher MPR; column 6 of Table 2.4 showed a positive but insignificant business-stealing effect, which results in a lower MPR and a wider confidence interval. The MSR estimates show much more uncertainty. Based on the estimates in column 2 of Table 2.3, the point estimate of the MSR is higher than the MPR, but the confidence interval is very wide. In column 6 of Table 2.3, the point

[15] For a detailed derivation and discussion, see Hall, Mairesse and Mohnen (2010).

2

estimate of knowledge spillovers from organisation capital is negative, leading to a lower MSR and an even wider confidence interval that includes zero. So despite the clearly positive private benefits to investment in organisation capital, the social benefits are much more uncertain and could well be less than the private return.

Table 2.7: The Marginal Social and Private Returns to OC Investment

	Column 2		**Column 6**	
MSR	0.636	[0.073 – 1.200]	0.155	[-0.710 – 1.026]
MPR	0.438	[0.337 – 0.540]	0.282	[0.153 – 0.411]

Notes: The marginal social return (MSR) and marginal private return (MPR) from investment in organisation capital are estimated using equations (2.10) and (2.11) and the parameter estimates as given in Tables 2.3 and 2.4 from the indicated columns. Reported in square brackets are the 95-percent confidence intervals, which are estimated using the delta method

2.3.5 Discussion

As mentioned in the introduction, we are not the first to analyse potential spillover effects from organisation capital or knowledge-based/intangible assets more in general. GHW find knowledge spillovers from U.K. industry stocks of 'economic competencies', which overlaps substantially with our measure of organisation capital.[16] CHJ find knowledge spillovers from non-R&D intangible assets using market sector capital stocks for the U.S. and European economies. Investment in non-R&D intangible consists in equal parts of investment in organisation capital (as we define it) and other intangible investments.[17]

The difference in asset coverage could account for the difference in findings, especially in comparison with the CHJ results: their knowledge spillovers could stem from many other assets than from organisation capital. But a first question would be whether their findings on knowledge spillovers could refer to knowledge spillovers from organisation capital given the lack of evidence for such spillovers in this study. GHW find some evidence of positive external effects, with industries learning about the organisational practices of their suppliers, but no support for the movements of workers between industries as a channel for external effects. GHW also find negative internal stock

[16]'Economic competencies' accounts for 80% of our measure of organisation capital and for 20% of investment of worker training.

[17]Specifically, investment in software, new architectural and engineering designs, development of new financial products, entertainment, artistic and literary originals, mineral exploration and worker training.

effects, which could be the same negative market-rival effect we find: investments in organisation capital by other firms in the industry adversely affect the investing firm.

There is a larger gap in findings with CHJ, who find evidence of positive productivity spillovers based on economy-wide data. If firm-level returns to scale are constant – as they are in our data – the findings of CHJ would point to between-firm spillovers. If such between-firm spillovers exist at the economy-wide level, this would imply that our analysis is not looking at the right channels through which knowledge about intangible capital 'spills over' between firms. Indeed, it could be that knowledge diffuses through the supply chain, through worker flows or in other ways that we cannot readily measure.

At its most limited, the contribution of this chapter is thus to show that there is no evidence to support the notion that firms with more similar technologies (as reflected in their patent portfolio) learn from each other's organisation capital. However, a corollary of this contribution is that any 'true' between-firm spillover channel cannot be positively correlated with the similarity of firm patent portfolios. Furthermore, such a true between-firm spillover channel also cannot be positively correlated with within-firm organisation capital, because if it were, we would have found (robust) evidence of increasing returns to scale in our basic production function estimates. Such a lack of correlation would be at odds with the literature on learning (e.g. Cohen & Levinthal, 1989), which argues that firms invest in R&D (in part) with the aim of learning about R&D done by other firms. Given that the hypothesised spillovers from organisation capital are also thought of as knowledge spillovers, a greater spillover potential should lead to greater within-firm investments in organisation capital. So, given our findings, it is not straightforward to hypothesise how knowledge spillovers from organisation capital would operate.

An alternative explanation would be that we measure organisation capital with greater error than CHJ or GHW. Such measurement error would make it harder for us to find significant evidence of knowledge spillovers. GHW and CHJ can certainly analyse more precisely-delineated measures of intangible capital than we are able to. Our investment measure, SGA, includes spending on advertising and managerial compensation – both of which GHW and CHJ also consider as investment in intangible assets – but also spending that is not related to intangible capital formation, such as rents. That said, the CHJ and GHW numbers are also imperfect measurements of 'true' organisation capital. It could be that having more and better-paid managers leads to the accumulation of more efficient organisational structures, but this is more of a presumption than a result. It is, for example, not known if firms that invest more in organisation capital (according to the CHJ/GHW measures) adopt more performance-enhancing management practices, as measured by Bloom and Van Reenen (2007). There is a positive correlation, though, between the quality of management practices and SGA-based measures of organisation capital, as shown by Eisfeldt and Papanikolaou (2013). This suggests that the measurement error in our SGA-based measure is not so large as to drown out a useful signal.

Furthermore it is not a given that measurement error would play a more substantial role in our firm-level setting given that we have many more observations (18,000 versus 100) and can more extensively control for confounding factors and employ econometrically appealing methods. Additionally, we can focus on firms in manufacturing, to which the production function framework can be more easily applied than to some of the services industries in the data of GHW, for which output prices are much harder to measure. Finally, GHW and CHJ both adjust their measure of output to include the estimated investment in intangibles. While this is logical within the framework of the System of National Accounts – investment goods have to be produced first – our focus on real sales as the output indicator has a much clearer interpretation: it is the sales to customers that brings in revenues – and thus can lead to profits – while the imputed output value of intangible capital investment is nothing more than an accounting element to balance the (national accountant's) books.

Given these considerations, it is hard to see how organisation capital could be a source of substantial knowledge spillovers. Especially the evidence from CHJ can most easily be interpreted as evidence of knowledge spillovers from 'non-R&D, non-organisation capital' intangible assets. The evidence of GHW was more mixed to begin with, with both negative and positive effects. We would thus argue that, first, our results place limits on where we can hope to find any knowledge spillovers from organisation capital; and second, that caution is in order when interpreting evidence of knowledge spillovers from intangible capital based on aggregate evidence.

2.4 Conclusions

This chapter presents the first firm-level analysis of knowledge spillovers from investment in organisation capital. With traditional tangible capital, aggregate productivity benefits are simply a summation of firm benefits, but when the asset is intangible – as is the case with organisation capital – there may be spillovers across firms that drive a wedge between the private and social returns of investment.

Our analysis is based on a sample of 1,266 U.S. manufacturing firms. We locate each firm in technology space, to capture potential knowledge spillovers of organisation capital between technologically similar firms; and in product market space to capture negative 'market-stealing' spillovers from competitors. We find no significant knowledge spillovers and only limited evidence for market-stealing effects on the market value of firms.

This lack of evidence stands in contrast to recent studies by GHW and CHJ that do find evidence for spillovers from intangible assets based on more aggregate data. We have argued that, at the very least, our findings limit the scope of where positive knowledge spillovers from organisation capital can be found. More broadly this chapter suggests that knowledge about organisation capital does not readily spill over between firms. This can be best understood if information about organisation capital is tacit, firm-specific and idiosyncratic. Seen in that light, it seems more sensible to interpret the evidence of GHW and CHJ as evidence in favour of knowledge spillovers from intangible assets other than organisation capital. Either way, the lack of supportive firm-level evidence on knowledge spillovers from organisation capital suggests caution is in order when looking for intangible assets as a potential accelerator of productivity growth.

Appendix

Table 2.8: Descriptive Statistics for a Sample Including Non-patenting firms

	Median	Mean	SD	Between SD	Within SD	Av.years	N
Sales	87	2,150	12,484	8,548	4,119	14.6	29,228
Market value	174	3,170	15,912	8,976	9,661	13.9	25,756
SGA expenses	22	331	1,279	810	558	12.4	23,839
R&D expenses	6	95	449	257	230	12.4	23,950
Physical capital	20	653	4,241	2,768	1,561	14.3	28,688
Employees	581	7,538	23,806	15,739	8,344	13.6	27,173
Internal OC stock	74	1,172	4,533	2,927	1,815	12.4	23,839
Internal RD stock	28	481	2,315	1,326	1,164	12.4	23,950

Notes: 'Between SD' illustrates the variation between firms (averaged over time), while 'Within SD' illustrates the variation over time, ignoring the between-firm variation. Sales are deflated by the industry price index and SGA expenses are deflated by the implicit GDP price deflator; all price indices are from the Bureau of Economic Analysis. Employees are in numbers; all other variables are in millions of 2005 U.S. dollars.

SGA: selling, general and administrative; *R&D*: research and development, *OC*: organisation capital; SD: standard deviation

Table 2.9: Production Function Estimates Including Non-patenting Firms

	(1)	(2)	(3)	(4)
Physical capital (K)	0.206***	0.239***	0.231***	0.251***
	(0.042)	(0.046)	(0.046)	(0.050)
Employees (L)	0.702***	0.492***	0.651***	0.476***
	(0.056)	(0.070)	(0.062)	(0.073)
Organisation capital (G)		0.246***		0.226***
		(0.046)		(0.055)
R&D capital (R)			0.072**	0.025
			(0.032)	(0.032)
Number of observations	18,171	13,994	14,058	13,994
Number of firms	1,432	1,232	1,233	1,232
R^2	0.664	0.731	0.720	0.729
Returns to scale (H^0: RTS=1)	0.908***	0.977	0.954*	0.979
Hansen J p value	0.48	0.103	0.588	0.178
Weak instrument	82.46	44.92	43.45	34.31

Notes: All results are estimated using on the two-step efficient generalised method of moments (GMM) estimator, using X_{it-2} and X_{it-3} as instruments for X_{it}. Dependent variable in all estimations is real sales and all specifications include firm and year fixed effects, the industry output index and the lag of the industry output index and the industry price index. Robust standard errors, clustered by firm, are shown in parentheses. Returns to scale tests whether the sum of all inputs (K, L and G and R where included) is significantly different from one. The Hansen J p value is based on a test of overidentifying restrictions, where the null hypothesis is that the instruments are valid. The Weak instrument line gives the Wald F-statistic of the first-stage regression. If this statistic exceeds 11–12 (depending on the specification), the IV bias is less than 5% of the bias of using OLS, see Stock and Yogo (2005).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.10: Sensitivity of Spillover Estimates to Removing Single Industries

Excluding industry:	(1) **Chemicals**	(2) **Computers**	(3) **Electrical**	(4) **Machinery**	(5) **Miscellaneous**
OC knowledge spillovers	–0.526	0.278	–0.174	–0.204	–0.304
	(0.446)	(0.501)	(0.431)	(0.600)	(0.424)
OC market rivals	–0.215**	–0.380***	–0.298***	–0.330***	–0.314***
	(0.091)	(0.121)	(0.092)	(0.103)	(0.092)
RD knowledge spillovers	0.759**	–0.0614	0.382	0.462	0.373
	(0.316)	(0.393)	(0.331)	(0.406)	(0.325)
RD market rivals	0.0632	0.091	0.048	0.056	0.054
	(0.059)	(0.068)	(0.059)	(0.065)	(0.059)
Physical capital (K)	0.160***	0.259***	0.173***	0.196***	0.210***
	(0.040)	(0.063)	(0.042)	(0.044)	(0.046)
Employees (L)	0.587***	0.542***	0.609***	0.579***	0.563***
	(0.067)	(0.097)	(0.065)	(0.070)	(0.071)
Organisation capital (G)	0.308***	0.296***	0.307***	0.314***	0.281***
	(0.064)	(0.078)	(0.054)	(0.063)	(0.057)
R&D capital (R)	–0.099**	–0.094*	–0.088**	–0.092**	–0.059
	(0.042)	(0.052)	(0.042)	(0.045)	(0.041)
Number of observations	11,303	7,821	13,100	12,195	12,533
Number of firms	871	626	1,038	973	981
R^2	0.823	0.564	0.756	0.751	0.755
Returns to scale (H^0: RTS=1)	0.956*	1.003	1.001	0.997	0.995
Hansen J p value	0.335	0.409	0.533	0.403	0.456
Weak instrument	24.01	12.55	21.51	22.96	28.82

Notes: The table shows the results from estimating equation (2.2), excluding a single industry at a time. Only the largest five industries are considered in this table, given that these (together) represent 80 percent of firms in the sample. The OC knowledge spillovers variable is based on equation (2.7) and the R&D knowledge spillovers variable is defined analogously. The OC market rivals is based on equation (2.9) and the R&D market rivals variable is defined analogously. *** p<0.01, ** p<0.05, *p<0.1

2

Table 2.11: Production Function Estimates Including Material Inputs

	(1)	(2)	(3)	(4)
Physical capital (K)	0.140***	0.160***	0.152***	0.154***
	(0.013)	(0.037)	(0.037)	(0.037)
Employees (L)	0.667***	0.557***	0.660***	0.549***
	(0.020)	(0.060)	(0.058)	(0.059)
Materials (M)	0.090***	0.066*	0.061*	0.056
	(0.012)	(0.036)	(0.036)	(0.036)
Organisation capital (G)		0.173***		0.238***
		(0.046)		(0.052)
R&D capital (R)			0.047	–0.058*
			(0.031)	(0.035)
Number of observations	11,831	9,755	9,790	9,755
Number of firms	924	831	832	831
R^2	0.814	0.832	0.822	0.834
Returns to scale (H^0: RTS=1)	0.897***	0.957*	0.859***	0.884***
Hansen J p value	0.001	0.154	0.338	0.224
Weak instrument	412.9	19.18	21.25	15.78

Notes: All results are estimated using on the two-step efficient generalised method of moments (GMM) estimator, using X_{it-2} and X_{it-3} as instruments for X_{it}. See notes to Appendix Table 2.9 for further details. *** p<0.01, ** p<0.05, *p<0.1

Table 2.12: Sensitivity of BSV Results to Sampling Cut-off and Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Production function			**Market value equation**		
	NW 1985-2000	NW 1981-2001	Clustered	NW 1985-2000	NW 1981-2001	Clustered
R&D knowledge spillovers	0.191***	0.241***	0.241***	0.381***	0.208**	0.208
	(0.046)	(0.039)	(0.068)	(0.113)	(0.090)	(0.148)
R&D market rivals	–0.005	0.007	0.007	–0.083***	–0.023	–0.023
	(0.011)	(0.010)	(0.017)	(0.032)	(0.026)	(0.048)
Physical capital (K)	0.154***	0.168***	0.168***			
	(0.012)	(0.013)	(0.021)			
Employees (L)	0.636***	0.644***	0.644***			
	(0.015)	(0.013)	(0.021)			
R&D capital	0.043***	0.038***	0.038***			
	(0.007)	(0.006)	(0.011)			
R&D capital/capital stock				0.806***	0.325*	0.325
				(0.197)	(0.174)	(0.248)
Number of observations	9,935	12,471	12,471	9,944	12,542	12,542

Notes: The columns 'NW 1985–2000' replicate the results from BSV, with production function estimates from Table V column (2) and market value equation estimates from Table III column (2) and, like BSV, using Newey-West HAC standard errors. The columns 'NW 1981–2001' correct the sampling cut-off error to cover all available data from BSV with Newey-West HAC standard errors. The columns 'Clustered' replace the Newey-West HAC standard errors by robust standard errors, clustered by firm. *** p<0.01, ** p<0.05, *p<0.1

2

CHAPTER 3

Complementarity between intangibles and ICT: Evidence from EU countries*

3

3.1 Introduction

Investment in information and communications technology (ICT) and investment in intangible assets are key sources of growth in advanced economies. Much anecdotal and firm-level evidence confirm that ICT and intangible assets do not only contribute to labour productivity growth individually, but do even more so in combination (Bloom et al., 2012; Bresnahan, Brynjolfsson & Hitt, 2002; Brynjolfsson & Hitt, 2000; Brynjolfsson, Hitt & Yang, 2002; Brynjolfsson & Hitt, 2003; Hall, Lotti & Mairesse, 2013). While evidence on this complementary relationship between investment in ICT and intangibles is well-established in microeconomic studies, little is known about this relationship at the macroeconomic level as there were no explicit data on intangible investment at the level of the economy or industries.[1] Since the pioneering measurement work of Corrado et al. (2005, 2009), which standardised and popularised the approach of measuring business investments in intangible assets, quantifying the impact of intangibles on productivity and economic growth has been made possible in recent years. Many researchers incorporate such assets into a standard 'sources-of-growth' framework and find that intangible capital contributes significantly to labour productivity growth (Borgo, Goodridge, Haskel & Pesole, 2013; Corrado et al., 2009; Fukao et al., 2009; Roth & Thum, 2013). However, the effect of labour productivity from the combined

*This chapter is based on Chen, Niebel and Saam (2016).

[1] To note, there have been other attempts to provide macroeconomic evidence on the complementarity between investment in ICT and intangibles (Basu et al., 2004; Corrado et al., 2014). This chapter however differs from the previous works, as this is the first study to explicitly account for intangible investment at the industry level. This is potentially a very useful source of variation that could help to pin down the complementary relationship between ICT and intangibles.

investment in ICT and intangibles is still not taken into account in those macroeconomic studies.

By using the industry-level intangible investment data for ten European countries, this chapter tests a much-discussed hypothesis in firm-level studies, namely that intangible capital investment is needed to gain the largest benefits from investment in ICT, and provides corroborating macroeconomic evidence. It is important to establish such evidence at the macroeconomic level as the existing microeconomic evidence may not hold in general and even if the findings can be generalised, the quantitative results could still differ if data with comprehensive coverage are used. We also contribute to the literature by shedding light on the magnitude of the output elasticity of intangible capital. Thus, in addition to its qualitative importance we also discuss the quantitative importance of intangible capital for labour productivity growth. More importantly, the quantitative implication enables us to quantify the growth differentials between industries with varying degrees of ICT intensity, which might be of great interest to policy makers in designing industry-specific policies.

This chapter is also related to the strand of literature that studies the productivity gap between the U.S. and continental Europe, as the poorer productivity performance observed in Europe since the mid-1990s may not only be the result of its lower level of investment in ICT relative to the U.S. (Van Ark et al., 2008), but also to a less effective exploitation of ICT due to lower investment in intangible capital.[2]

To empirically examine to what extent the growth impact of intangible capital is dependent on an industry's ICT intensity, we first define an industry characteristic that ranks the industries by the extent to which they rely on the use of ICT and calculate this ranking as the ratio of ICT capital services to labour services. The resulting intensity indicator is then interacted with the growth of intangible capital and the interaction term is estimated in an intangibles-augmented Cobb-Douglas production function. Under the assumption of constant returns to scale, we test whether a one percent increase in intangible capital deepening increases output per worker more strongly in more ICT-intensive industries.

Three key findings emerge from this study. First, intangible capital contributes systematically to labour productivity growth and its productive impact is found to be significantly higher in ICT-intensive industries than in those that use little ICT. This result supports the complementarity between intangible capital and ICT in production

[2] According to Corrado, Haskel, Jona-Lasinio and Iommi (2013) the U.S. has a much higher propensity to invest in intangibles than the EU. Between 1995 and 2009 (the period during which the productivity gap widens), intangible investment as a share of GDP is averaged around 10.6% for the U.S., while the share is only about 6.6% for the EU.

found in prior microeconomic studies. Second, using industry-level instead of country-level data on intangibles, we find a much smaller mean output elasticity of intangible capital (0.17 as opposed to 0.4–0.7 found in Corrado et al., 2014), as well as a larger differential effect of labour productivity growth across industries. The output elasticity of intangible capital amounts to 0.099 for industries at the lowest quartile of ICT intensity, while it exceeds 0.19 for industries at the highest quartile. Third, by distinguishing various different intangible asset types, we find that not every single intangible asset exhibits a higher output elasticity in ICT-intensive industries. In the sample of assets investigated, this is only true for organisational structures and research and development (R&D).

The remainder of this chapter is organised as follows. Section 3.2 discusses the concept and measurement of intangible capital and how capitalisation of intangibles changes the traditional output measure and growth accounting framework. The econometric approach to investigate the impact of intangible capital accumulation on labour productivity growth is outlined in Section 3.3. Section 3.4 elaborates on the proxy of industry ICT intensity measures. Empirical analysis and robustness checks are presented in Section 3.5. Section 3.6 concludes.

3.2 Measuring intangible inputs and output

This section considers issues related to the concept and measurement of intangible capital. It begins with a discussion on the definition of intangible capital: what is it and how can it be measured? Then, it outlines how capitalising investment in intangible assets changes the conventional output measure, followed by a descriptive overview of the data used for analysis. It is important to emphasise that this section only highlights the main issues, readers should refer to Niebel et al. (2013) for more extensive details regarding the construction of the intangible investment data by industry.

3.2.1 Defining intangible capital

Intangible capital, also known as knowledge-based capital, comprises a variety of distinctive assets, which create long-lasting benefits for the firm and the economy. Unlike machinery, equipment, and buildings, intangible assets do not have a physical embodiment. Well-known examples of intangible assets include computer software and scientific research and development (R&D), both of which are currently recognised as part of the official national accounts of a country.[3] Since the ground-breaking work of Corrado et al. (2005), a more comprehensive measure of intangible capital that is compatible with national accounts has been developed and it consists of three categories: (1) computerised information, (2) innovative property, and (3) economic competencies.[4] The first category mainly includes investment in software and computerised databases. The second is composed of scientific R&D and a number of non-scientific R&D, such as new financial products, designs, and artistic originals. The last category, arguably the largest in size, contains brand equity, firm-specific human capital and organisational structures.

Table 3.1: Industry Coverage

Industries covered (NACE Rev. 1.1 classification)	**Acronym**
Agriculture, hunting, forestry and fishing	(AtB)
Mining and quarrying	(C)
Total manufacturing	(D)
Electricity, gas and water supply	(E)
Construction	(F)
Wholesale and retail trade	(G)
Hotels and restaurants	(H)
Transport and storage and communication	(I)
Financial intermediation	(J)
Renting of machinery and equipment and other business activities	(K)
Other community, social and personal services	(O)

This measurement breakthrough by Corrado et al. (2005) sparked great interests among economists and unleashed increasing efforts to measure overall business investment in intangibles, which in the end led to the development of the INTAN-Invest database (Corrado et al., 2012). It provides market sector data on the above-mentioned intangible assets for 27 EU countries plus Norway and the U.S. The data set used in this chapter is a breakdown of the INTAN-Invest database by industry and it was developed by Niebel et al. (2013) in the INDICSER project.[5] This data cover eleven industries according to the NACE 1.1 classification (see Table 3.1) and seven different intangible assets that are not included in the EU KLEMS database,[6] where the industry-level data on output, non-ICT assets, ICT assets, and labour input are derived from (see Table 3.2

[3]Software has been recognised as investment in national accounts since the 1993 revision of the System of National Accounts (SNA); R&D has been newly added since the SNA 2008 revision.

[4]The need to measure and incorporate these intangible assets into national accounts is also extensively discussed in Nakamura (2010).

[5]INDICSER refers to Indicators for Evaluating International Performance in Service Sectors.

[6]The EU KLEMS database provides detailed statistics on growth and productivity accounts at industry level for individual EU member states, various EU aggregates, Japan, and the United States. See O'Mahony and Timmer (2009) for more details.

Table 3.2: ASSET GROUPS

Non-ICT Assets	**ICT Assets**	**Intangible Assets**
Transport equipment	Computing equipment	Scientific research and development
Other machinery and equipment	Communications equipment	Firm-specific human capital
Total non-residential investment	Software	New financial product development
Residential structures		New architectural & engineering designs
Other assets		Market research
		Advertising expenditure
		Organisational structures (Own Account)
		Organisational structures (Purchased)

Notes: The composition of ICT and non-ICT assets is consistent with the distinction made in EU KLEMS database see O'Mahony and Timmer (2009).

and further discussions on these variables in Section 3.3). The term 'new intangibles' is used to designate those investments that are not capitalised in national accounts prior to the SNA 2008 revision. As a result, computer software is counted as part of ICT assets instead of 'new intangibles' in this chapter.

3.2.2 Measurement approach

Measuring business investment in intangibles is extremely difficult as they are often created for internal use and suffer from a lack of observable market transaction data for valuation. To circumvent this problem, the cost approach has been widely used as an alternative. The underlying assumption of the cost approach is that firms are willing to invest in intangible assets until the discounted present value of the expected future income stream equals to the cost of producing the marginal asset (Jorgenson, 1963). A key challenge and caveat of the cost approach, however, is that it is not known how much (i.e. what portion) of intangible spending can be counted as investment. The current consensus is to apply a capitalisation factor equal to one. That is, all expenditures on intangibles are believed to have long-lasting impacts (i.e. longer than a year) and are counted as investment.[7]

To convert nominal values into real terms, a price deflator for intangible investment is needed. Following the broader literature on intangibles, we use an output deflator that

[7] Known exceptions to this rule are spending on advertising and own-account organisational structures. Existing research on advertising suggest that only about 60% of advertising expenditures have a long-lasting impact (i.e. longer than one year). As for own-account organisational structures, 20% of managers' wage are counted as investment (Corrado et al., 2005).

is based on the value added price index for the total business sector as the proxy.[8] The industry-specific intangible capital stock is then constructed using the usual perpetual inventory method (PIM):

$$R_{k,i,t} = (1-\delta_k)\cdot R_{k,i,t-1} + \frac{N_{k,i,t}}{p_t} \tag{3.1}$$

where $R_{k,i,t}$ is the capital stock for intangible asset k in industry i at time t. Nominal investment in intangibles N is deflated by the value added price deflator p_t obtained from the EU KLEMS database (except for training, see footnote 8). This deflator is assumed to be the same across all industries and asset types. δ_k is the time– and industry–invariant depreciation rate for asset k, following Corrado et al. (2012). By assuming that the economy is in a steady-state, the initial capital stock in year 1995 is calculated by the following relationship:

$$R_{k,i,1995} = \left(\frac{N_{k,i,1995}}{p_{1995}}\right) \Big/ (\delta_k + \overline{g}) \tag{3.2}$$

where $\overline{g}$ is the average rate of growth of real value added in the total business sector between 1991 and 1999. Under the assumption of marginal productivity pricing, (industry) output measured by nominal value added is accordingly expanded as follows:

$$\mathrm{VA}_{adj,i,t} = \mathrm{VA}_{i,t} + \sum_{k\in INT} N_{k,i,t} \tag{3.3}$$

where the conventional output measure $\mathrm{VA}_{adj,i,t}$, taken from EU KLEMS, is augmented to include the flow of new intangibles $N_{k,i,t}$. Thus, after capitalisation intangible capital is both a productive input ($R_{k,i,t}$) that provides capital services and a part of adjusted output ($N_{k,i,t}$). To convert the nominal adjusted value added to volumes, an adjusted value added deflator is required and it is calculated as:

$$\Delta ln\mathrm{VA\_}P_{adj,i,t} = \overline{v}_{\mathrm{VA},i,t}\Delta ln\mathrm{VA\_}P_{i,t} + \overline{v}_{\mathrm{INT},i,t}\Delta lnP_{i,t} \tag{3.4}$$

where $\overline{v}_{\mathrm{VA},i,t}$ is the two-period average share of nominal value added in adjusted value added, and $\overline{v}_{\mathrm{INT},i,t}$ is the two-period average share of nominal intangible investment N in adjusted value added.

The internal rate of return *irr* for each industry i also needs to be recalculated and it is redefined as follows:

[8] The exception is investment in firm-specific human capital, which is deflated using an earnings deflator following O'Mahony (2012). The rationale for using an earnings deflator for investment in training is that training costs are related more to wage payments than to prices in general.

$$irr_{i,t} = \frac{(\mathrm{VA}_{adj,i,t} - LAB_{i,t})_{adj,i,t} + \sum_k \left(p^I_{k,i,t} - p^I_{k,i,t-1}\right) R_{k,i,t} - \sum_k p^I_{k,i,t}\delta_{k,i}R_{k,i,t}}{\sum_k p_{k,i,t-1}R_{k,i,t}} \tag{3.5}$$

where the adjusted value added VA_{adj} minus the labour compensation (LAB) denotes the industry-specific adjusted total capital compensation; p, δ, and R are the investment price index, the rate of depreciation and the real stock of both tangible and intangible assets k. The asset-specific user cost of capital $uc_{k,i,t}$ is calculated using the following relation:

$$uc_{k,i,t} = p^I_{k,i,t-1} \cdot irr_{i,t} + p^I_{k,i,t} \cdot \delta_{k,i} - [p^I_{k,i,t} - p^I_{k,i,t-1}] \tag{3.6}$$

As equation (3.6) shows, the user cost of capital is determined by the nominal rate of return, the rate of depreciation, and the asset-specific capital gains. The user cost, in turn, is used to calculate the capital compensation for each asset type and industry:

$$COMP_{adj,i,t} = uc_{k,i,t} \cdot R_{k,i,t} \tag{3.7}$$

3

The industry-specific growth of each intangible capital services R^s is calculated as follows:

$$\Delta lnR^s_{i,t} = lnR^s_{i,t} - lnR^s_{i,t-1} = \sum_{k \in INT} \overline{w}^{\mathrm{INT}}_{ki,i,t} \Delta lnR_{k,i,t} \tag{3.8}$$

where $\overline{w}^{\mathrm{INT}}_{k,i,t}$ is the two-period average share of intangible asset k in total intangible capital compensation.

The aggregation of input and output volumes to the total business sector is calculated based on the Törnqvist quantity index as described in O'Mahony and Timmer (2009)

$$\Delta lnR^s_{BS,t} = \overline{u}^{\mathrm{INT}}_{i,t} \sum_i lnR^s_{i,t} \tag{3.9}$$

where $\overline{u}^{\mathrm{INT}}_{i,t}$ is the two-period average share of industry i in total business sector intangible capital compensation.

3.2.3 Price and depreciation issues

The growth of intangible capital stocks and services calculated above may be sensitive to the assumptions on price deflation and depreciation rates. As widely acknowledged, the overall business output price is only a place-holder when used as the price index for intangible investment. It could be argued that rather than the business-sector price deflator, more appropriate asset deflators would be the price indices of the industries that produce (in part) intangible assets, such as the management consulting (organisation capital), advertising (brand equity) and architectural and engineering services (architectural designs) industries. Although this might not be a perfect match, especially for own-account investment, a similar procedure is used to deflate investment in own-account software in the national accounts of countries like the United States. Appropriate output deflators for intangible-producing industries, however, are not widely available for the set of EU countries that we cover.

In order to assess the plausibility of the assumption that the growth of intangible capital stocks is robust to changing the deflator from the overall business output deflator to output deflators of intangible-producing industries, we use data for the U.S., where more detailed industry prices are available. Intangible capital stocks are reconstructed for investments in R&D, advertising, market research, organisation capital, and architectural design and engineering services. One of the findings is that the growth of intangible capital stock calculated using the business-sector price deflator correlate very highly with the growth of the stock calculated using detailed industry-specific prices (i.e. correlations are all above 0.92). Although the degree to which this analysis holds true for other countries is unknown, it does provide comforting evidence that the scope of bias resulting from the choice of the price deflator is likely to be limited. As for the depreciation rates, these are the ‘standard’ rates used in all research on intangibles. The sensitivity of capital stock growth to changing the standard depreciation assumptions seems minor, as shown in studies like O’Mahony (2012).

3.2.4 Descriptive statistics

The industry intangible investment data cover ten European countries and for the period of 1995-2007: Austria, Czech Republic, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, and the United Kingdom. One of the key insights of the industry data is that investment in intangibles is found to be concentrated most intensively in Manufacturing industry (D), which has an average share of total intangible investment of 38 percent across ten EU countries (see Table 3.3). This result is in line with the work of Goodridge et al. (2012b) who find that the Manufacturing industry has the highest ratio of intangible investment to value added. The Business service industry (K) and the Wholesale and retail trade industry (G) also show relatively large shares of intangible investment in comparison to other industries. With an average share of less than 0.3 percent, the Mining and quarrying (C) industry has the lowest level of investment in intangible capital.

Table 3.3: Average Share of Intangible Investment in Total Business Sector

Industry	AT	CZ	DK	FI	FR	DE	IT	NL	ES	UK	*Mean*
AtB	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.009
C	.00	.01	.00	.00	.00	.00	.00	.01	.00	.01	.003
D	.38	.29	.34	.60	.33	.57	.35	.32	.39	.22	.379
E	.01	.02	.01	.02	.02	.02	.01	.02	.03	.01	.017
F	.05	.08	.09	.03	.04	.03	.05	.04	.07	.05	.053
G	.16	.15	.17	.08	.12	.08	.21	.14	.12	.14	.137
H	.02	.02	.01	.01	.01	.01	.02	.02	.03	.03	.018
I	.05	.05	.06	.06	.06	.03	.07	.09	.08	.08	.063
J	.09	.09	.07	.06	.10	.10	.07	.09	.11	.15	.093
K	.20	.24	.19	.10	.27	.14	.18	.22	.12	.25	.191
O	.04	.04	.04	.03	.03	.02	.04	.04	.04	.06	.038

Source: Niebel et al. (2013). The last column *Mean* is calculated as the cross-country average.

3

Table 3.4 provides some basic descriptive statistics on the key variables of interest. As can be seen in this table, the most rapid growth of inputs over the period of observation is found for ICT capital (with an average growth rate of 12 percent). Although the growth is much slower than for ICT, growth in intangible capital input is the second largest. It grew by over 4 percent between 1995 and 2007. The amount of labour services provided, on the other hand, experienced the slowest growth. It grew by an average of merely 1 percent over the same period.

Table 3.4: Growth Rates of the Key Variables

	Median	Mean	S.D.	Min	Max	N
Value added	0.03	0.02	0.06	–0.55	0.34	1,320
Non-ICT	0.02	0.02	0.04	–0.40	0.19	1,320
ICT	0.10	0.12	0.10	–0.23	0.85	1,320
Total intangibles	0.04	0.04	0.06	–0.23	0.63	1,320
Labour	0.01	0.01	0.04	–0.24	0.15	1,320

Notes: Value added is adjusted to include intangible capital as in equation (3.3). Growth rates are calculated as *ln* differences and are averaged over the period 1995-2007. The letter N in the last column denotes the total number of observations. Note, the actual number of observations is 1430 (10 countries times 11 industries times 13 years), but one year is lost for computing the growth rate.

3.3 Econometric approach

The main model of interest builds upon the following general production function:

$$V_{c,i,t} = A_{c,i,t} \cdot F(L_{c,i,t}, \boldsymbol{K}_{c,i,t}) \tag{3.10}$$

where V denotes value added adjusted to include intangible capital.[9] A is the Hicks-neutral technology parameter that allows for changes in productivity with which labour (L) and capital (K) are transformed into output. The subscripts c, i, t indicate country, industry, and year. Suppose total capital input $\boldsymbol{K}$ is composed of three types: non-ICT (NICT), ICT, and intangible capital (INT) and assume a Cobb-Douglas functional form for the production function. Equation (3.10) can be written out as follows:

$$V_{c,i,t} = A_{c,i,t} \cdot L^{\alpha}_{c,i,t} \left(K^{NICT}_{c,i,t}\right)^{\beta_1} \left(K^{ICT}_{c,i,t}\right)^{\beta_2} \left(K^{INT}_{c,i,t}\right)^{\beta_3} \tag{3.11}$$

where L denotes labour input measured by labour services, which accounts for differences in labour qualities (i.e. human capital);[10] $\boldsymbol{K}$ is the capital services provided by non-ICT, ICT, and intangible capital. The output elasticities are labelled by the superscripts α and $\beta_x,\ x = (1, 2, 3)$. After taking logs and first differences and assuming constant returns to scale, equation (3.11) can be rewritten as:

$$\Delta(v - l) = \beta_1 \Delta(k^{NICT} - l) + \beta_2 \Delta(k^{ICT} - l) + \beta_3 \Delta(k^{INT} - l) + \mu \tag{3.12}$$

where lower-case denotes variables in natural logarithms and the subscripts are suppressed for simplicity of exposition. The efficiency term A is modelled as part of the error term μ. For reasons explained below, the error term is decomposed into a country-industry specific fixed effect $\omega_{c,i}$, a full set of time dummies τ_t, and an idiosyncratic component $\epsilon_{c,i,t}$. To examine whether the output elasticity of intangible capital differs across industries with varying degrees of ICT intensity, intangible capital is interacted with an ICT intensity indicator ($D^{ICT}_{c,i}$) that is measured as the ratio of ICT capital services to labour services:[11]

[9]Value added is used as the output measure because: (1) there is no readily available intangibles data on gross output; and (2) labour productivity based on value added is measured more accurately in the presence of outsourcing, a feature that is commonly observed at the industry level (Schreyer & Pilat, 2001)

[10]Labour input is taken from the EU KLEMS database which adjusts for the productivity of various types of labour input such as low- versus high-skilled. EU KLEMS cross-classifies labour input by educational attainment, gender, and age, resulting in a total of 18 different labour categories. Interested readers should refer to O'Mahony and Timmer (2009) for more details.

[11]This is one of the most commonly used measures for (ICT) capital intensity (e.g. Corrado et al., 2014). Other proposed measures, such as ICT capital compensation as a share of total value added (e.g. Jorgenson & Timmer, 2011; Michaels, Natraj & Van Reenen, 2014) and ICT capital share of total

$$\Delta(v-l) = \beta_1\Delta(k^{NICT}-l) + \beta_2\Delta(k^{ICT}-l) + \beta_3\Delta(k^{INT}-l) \\ + \gamma\Delta(k^{INT}-l)\cdot D^{ICT}_{c,i} + \omega_{c,i} + \tau_t + \epsilon_{c,i,t} \tag{3.13}$$

This specification is akin to the difference-in-differences approach which has its antecedents in literature that analyses the impact of financial development on industry growth (Rajan & Zingales, 1998)[12] and has been used in the previous work on productivity in ICT-intensive industries (Corrado et al., 2014). If the complementarity hypothesis holds true, γ is expected to be positive and statistically significant. Given that ICT investment is highly correlated with intangible investment (the correlation coefficient is larger than 0.8), one may argue that it is perhaps not intangible capital that has a higher output elasticity in ICT-intensive industries but ICT investment itself or even non-ICT assets. To account for these potential omitted variable biases, the full model is specified as follows:

$$\Delta(v-l) = \gamma_1\Delta(k^{NICT}-l)\cdot D^{ICT}_{c,i} + \gamma_2\Delta(k^{ICT}-l)\cdot D^{ICT}_{c,i} \\ + \gamma_3\Delta(k^{INT}-l)\cdot D^{ICT}_{c,i} + \beta\mathbf{X}' + \omega_{c,i} + \tau_t + \epsilon_{c,i,t} \tag{3.14}$$

where $\mathbf{X}'$ indicates the vector of the main variables including the growth of capital inputs. γ_1 and γ_2 are not expected to be different from zero, as there is no theoretical underpinning for assets other than intangibles to complement ICT investment. To ensure a meaningful interpretation of the coefficients of the variables of interest, the interaction terms are demeaned for estimation following the suggestion of Balli and Sørensen (2013).[13]

It is important to note that the econometric specification presented above has several limitations. First, assuming a Cobb-Douglas production function is equivalent to assuming a constant output elasticity. This differs from the typical growth accounting framework where output elasticities, approximated by the cost shares, can change over time. Allowing for changing output elasticities, though, would require the use of a translog production function. Despite its greater flexibility, estimating a translog production function comes at the cost of a larger number of parameters that need to be estimated. Having distinguished four different production factors (i.e. three capital inputs plus labour input), the amount of parameters that need to be estimated in

capital services (e.g Stiroh, 2002), are considered in sensitivity analysis.

[12]For a more extensive review on using the difference-in-differences estimation approach and its pros and cons, see Ciccone and Papaioannou (2010)

[13]From an econometric point of view, demeaning the interaction term does not change the result. It is a reparameterisation of the same statistical model, but the added benefit is that the coefficient estimates of the main variables will remain similar to the simple model without the interaction term. As for the coefficient estimate of the interaction term as well as its standard errors, it will be exactly identical whether the interaction variables are demeaned or not.

a translog framework increases to 14, imposing hard constraints on the feasibility of the analysis.[14] The probability of the occurrence of a harmful collinearity between the explanatory variables significantly increases as the number of considered production factors increases. Given this practical constraint, estimating a Cobb-Douglas production function remains preferred in spite of the assumption of a constant output elasticity.

Another issue in the estimation of equation (3.14) is the potential correlation between unobservable productivity shocks and the input levels, as was first noted by Marschak and Andrews (1944) and further discussed in Griliches and Mairesse (1998). This problem is commonly referred to as simultaneity bias in production function estimation. It arises from the fact that unobservable productivity shocks are known to the firms, but not to the econometrician when firms choose their input levels. Firms facing a positive productivity shock may respond by using more inputs. Negative shocks, on the other hand, may lead firms to cut back their output by decreasing input use. To control for this simultaneity bias, it is advised to include time dummies and (the country-industry specific) fixed effects in the error term (Ackerberg, Benkard, Berry & Pakes, 2007). The rationale for this is that to the extent that the observable productivity shocks are time-invariant and country-industry specific, this specification should go a long way towards dealing with the problem of simultaneity bias. This within estimator is also preferred to the between estimator, as by collapsing the time series as an average it would lead to a too small number of observations (i.e. 110), resulting in a larger scope for simultaneity bias than the within estimator.

Following Michaels et al. (2014), we further account for the potential endogeneity of the ICT intensity indicator $D_{c,i}^{ICT}$ by instrumenting the measure with the industry-level U.S. values at the beginning of the period of observation. The idea behind this strategy is that the sharp decline in quality-adjusted ICT prices disproportionately affects industries that have a greater potential for using ICT inputs. An indicator of this potential, as argued by Michaels et al. (2014), is the initial ICT intensity in the U.S., a country that is widely seen as the technological leader. Last but not least, standard errors are corrected for heteroskedasticity and correlation between the country-industry pairs, an approach also applied by Stiroh (2002) in investigating the revival of the U.S. productivity growth using industry-level data.

[14] In translog production function estimation, the number of estimated parameters is equal to $n \cdot (n+3)/2$, where n denotes the number of production factors.

3.4 Proxy ICT intensity indicator

Following the literature, there are various ways to proxy for country-industry variant ICT intensities: (1) the ratio of ICT capital services to labour services, (2) the ICT capital share – of total value added, (3) – of total capital services, and (4) – of total capital compensation (Table 3.5).

Table 3.5: Definition of ICT Intensity Indicators

$\mathbf{D^{ICT}} \equiv$ **ICT intensity indicator**	
$^{*}(1)D_1^{ICT} = \dfrac{\overline{W}^{ICT}K^{ICT}}{LS}$	$^{\S}(2)D_2^{ICT} = \dfrac{p^{ICT}K^{ICT}}{p^{ICT}K^{ICT} + p^{NICT}K^{NICT} + WL}$
$^{*}(3)D_3^{ICT} = \dfrac{\overline{W}^{ICT}K^{ICT}}{\overline{W}^{ICT}K^{ICT} + \overline{W}^{NICT}K^{NICT}}$	$^{\S}(4)D_4^{ICT} = \dfrac{p^{ICT}K^{ICT}}{p^{ICT}K^{ICT} + p^{NICT}K^{NICT}}$

$^{*}\overline{W}$ is the two-period ICT capital compensation share in total nominal capital compensation; K^{ICT} and K^{NICT} denote capital stocks. LS indicates labour services measured by total number of hours worked.

$^{\S}P$ is the rental price of capital stock. The superscripts denote capital types: namely ICT and non-ICT. WL indicates the labour share of income.

On theoretical grounds, there is no proxy that is superior to the others. We follow Corrado et al. (2014) in using ICT capital services divided by labour services as the baseline measure of ICT intensity and apply the other three alternative measures for sensitivity analysis. Figure 3.1 displays the average values of all four intensity measures. If ICT intensity is split at the median intensity value, Transport (I), Financial intermediation (J), and Business services (K) would be classified as ICT-intensive industries across all four measures; while Agriculture (AtB), Manufacturing (D), and Construction (F) are always ICT non-intensive. Mining and quarrying (C) remain below the median value for three measures.[15]

Since the ICT intensity might be endogenous, we follow Michaels et al. (2014) in using the industry-specific U.S. ICT intensity at the beginning of the period of observation (i.e. 1995) as an instrument. For comparison purposes, analysis using the endogenous indicator – the average of ICT intensity across ten EU countries and time – is also carried out, but instrumentation with the U.S. values remains to be the benchmark specification. The U.S. ICT capital intensity in 1995 is shown in Figure 3.2. Comparing this industry ranking to the ranking of average EU ICT intensities in the upper left panel of Figure 3.1, the main differences are the higher position for industry D and the

[15]Results for individual countries are available upon request. For the preferred measure, the values for industries J and K exceed the median in nine out of ten countries and the values for industry I in eight countries. The values for industries AtB, F, and H fall below the median in all countries. The values for Manufacturing (D) tend to lie close to the median.

lower position for industry C in the U.S. in 1995, while other industries remain largely unchanged.

Figure 3.1: Four Measures of EU Industry ICT Intensity

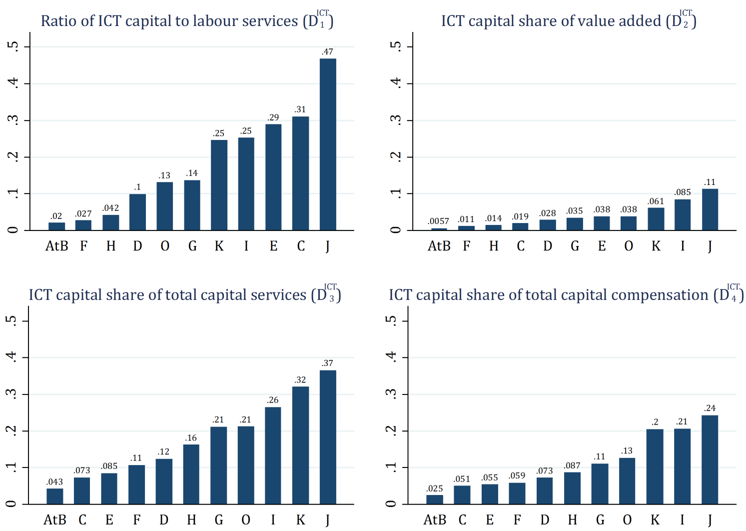
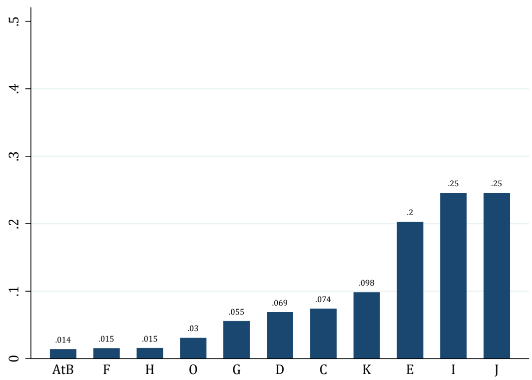


Figure 3.2: U.S. Industry ICT Intensity in 1995



These ICT intensity measures vary continuously, both across industries and over time. This could lead to volatility in an industry's ranking. As an alternative to these continuous ICT intensity indicators, we also use a discrete indicator by grouping industries into ICT-intensive and ICT non-intensive in the spirit of Stiroh (2002) and Bloom et al. (2012). This helps to keep the volatility of an industry's ranking to a minimum. At the same time it remains an accurate description of the actual ranking of ICT intensities, as the changes are likely to occur within rather than between the intensity groups. Using the ratio of ICT capital to labour services as the preferred proxy (i.e. D_1^{ICT}), three alternative criteria can be applied to distinguish ICT-intensive industries from those that are ICT non-intensive. The first one is the standard practice of dividing the groups at the median value of ICT intensity (observed in industry G). Industries with ICT-intensity values larger than 0.14 are labelled as ICT-intensive industries (i.e. K, I, E, C, J); while others with intensity values smaller than the median are labelled as ICT non-intensive (i.e. AtB, F, H, D, O). For robustness checks, we also looked for 'structural breaks' of the intensity values and used that criterion to split the industries. The two largest structural breaks are observed in industries D and K. For the former, the ICT intensity value became more than twice as large as the preceding industry H; while for industry K, it is about 80 percent more ICT-intensive than the preceding industry G.

Table 3.6: Discrete Measures of ICT Intensity

	Split at median (G)	Split at break point (D)	Split at break point (K)
ICT-intensive	K, I, E, C, J	D, O, G, K, I, E, C, J	K, I, E, C, J
ICT non-intensive	AtB, F, H, D, O	AtB, F, H	AtB, F, H, D, O, G

3.5 Empirical results

This section discusses the main empirical findings. It begins with the analysis on the importance of intangible capital for labour productivity growth, followed by the test whether the output elasticity of intangible capital is higher in industries that invest more in ICT. It provides a brief discussion on the quantitative implication of the results and on how it differs from Corrado et al. (2014). By distinguishing various different intangible asset types, this section ends with the analysis on which specific intangible asset is most conducive to the exploitation of ICT investment.

3.5.1 Analysis for total intangible capital

Table 3.7 presents the first set of results. Under the assumption of constant returns to scale, columns (1) and (2) estimate the Cobb-Douglas production function, first without intangibles and then adding them. Both non-ICT and ICT capital are found to be significantly associated with labour productivity growth. In the augmented estimation in column (2), intangible capital is also identified as an important driver of labour productivity growth, a result conforming to the rapidly growing literature calling for an equal treatment of intangible investment vis-à-vis the tangible counterparts (Corrado et al., 2005; Van Ark et al., 2008; Niebel et al., 2013).

Table 3.7: Cobb-Douglas Production Function Estimation

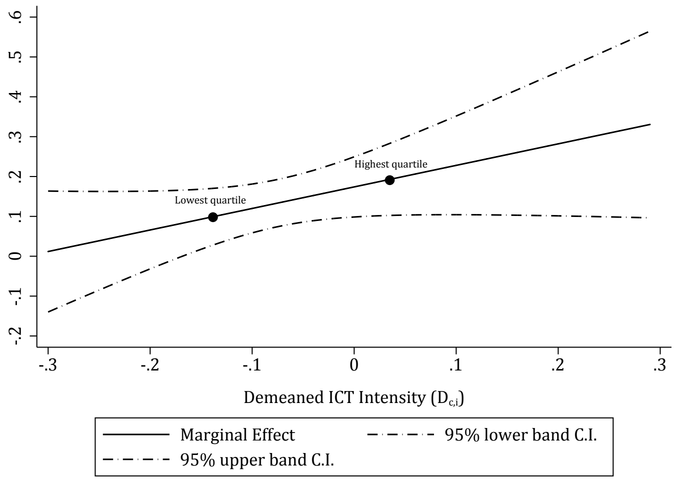
	(1) Two–capital	(2) INT augmented	(3) Full	(4) Full
	OLS	OLS	OLS	IV
$NICT_{c,i,t}$	0.372***	0.313***	0.312***	0.306***
	(0.050)	(0.048)	(0.049)	(0.055)
$ICT_{c,i,t}$	0.087***	0.080***	0.066***	0.075***
	(0.026)	(0.025)	(0.024)	(0.028)
$INT_{c,i,t}$		0.130***	0.161***	0.174***
		(0.031)	(0.034)	(0.038)
$NICT_{c,i,t} \times D^{ICT}_{c,i}$			–0.060	0.057
			(0.284)	(0.389)
$ICT_{c,i,t} \times D^{ICT}_{c,i}$			–0.207**	0.001
			(0.088)	(0.224)
$INT_{c,i,t} \times D^{ICT}_{c,i}$			0.340*	0.540*
			(0.193)	(0.317)
Year Dummies	Yes	Yes	Yes	Yes
N	1,320	1,320	1,320	1,320
Adjusted R^2	0.187	0.209	0.214	0.206
F statistic for excluded instruments				7.96

Notes: The output V (i.e. value-added) in column (1) is not adjusted for the inclusion of intangible capital; whereas for column (2)–(4), intangibles are added both as an input and as an output. Hence, output V is adjusted for intangibles in these columns. All specifications in column (1)-(4) include the country-industry specific fixed effect and the interaction terms are in demeaned forms. Standard errors shown in parentheses are heteroskedastic-robust to country-industry clustering. Column (3) and (4) calculate the industry ICT intensity as the ratio of ICT capital services to labour services. Column (3) uses the 'endogenous' ICT intensity indicator measured as the time average across all EU country-industry pairs. Column (4) instruments for the industry ICT intensity using the industry-level measures of ICT from the U.S. in 1995. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

The differential impact of intangible capital across industries with varying degrees of ICT intensity is revealed in columns (3) and (4). The former uses the 'endogenous' industry ICT intensity indicator, calculated as a time average across all EU country-industry pairs. Column (4), as the baseline specification, employs the 'exogenous' ICT intensity values from the U.S. as instrument. The interaction between intangible capital growth and ICT-intensity (i.e. γ_3) is found to be positive and significant in both 'endogenous' and 'exogenous' specifications. Meanwhile, no (robust) evidence is found for ICT and non-ICT capital. This suggests that the output elasticity of intangible capital is, as expected, significantly larger in industries characterised by higher levels of investment in ICT. In other words, among all capital inputs only intangible capital exhibits a higher output elasticity in ICT-intensive industries. With a larger coefficient, this complementarity effect seems to be stronger in the baseline specification when the ICT intensity is instrumented with the exogenous U.S. values (see column 4 in Table 3.7). Since the interaction terms are demeaned for estimation, the main effect of intangible capital represents the output elasticity of an industry with average ICT intensity, which amounts to 0.174.

The positive correlation between the ICT intensity and the output elasticity of intangible capital is visualised in Figure 3.3 where the partial effect of intangibles is plotted against the (demeaned) ICT-intensity defined by country-industry pairs. The upward sloping line suggests that the output elasticity of intangible capital goes hand in hand with the level of investment in ICT. The demeaned ICT intensity at the lowest quartile is (minus) 0.138, which corresponds to an output elasticity of 0.099. At the highest quartile, the demeaned ICT intensity takes the value 0.35 and the output elasticity amounts to 0.193. Since ICT intensities assume very high values in some country-industry pairs, the output elasticity at the 90th percentile (a demeaned intensity value of 0.22) rises to nearly 0.3.[16]

Figure 3.3: MARGINAL EFFECT OF INTANGIBLE CAPITAL



[16]This is derived by taking derivatives with respect to intangible capital in equation (3.14). Doing so, one arrives at $\hat{\beta}_3 + \hat{\gamma}_3 \cdot D_{c,t}$, where $D_{c,t}$ refers to the demeaned ICT intensity. Plugging in the estimates obtained under column (4) in Table 3.7, an output elasticity of 0.099 at the lowest quartile and 0.193 at the highest quartile are obtained for intangible capital.

As argued in the previous section, various ICT intensity indicators have been suggested in the past. If the output elasticity of intangible capital is truly different across industries with varying degrees of ICT-intensity, this finding should be robust to these alternative ICT intensity measures. Table 3.8 provides comforting results. No matter which ICT intensity measure is used, the output elasticity of intangibles is consistently higher in more ICT-intensive industries. This is true whether the endogenous ICT intensity measure is used or the instruments of the U.S. values are used.[17] The results are also robust to discretely splitting industries into ICT-intensive and ICT non-intensive groups using various alternative grouping criteria (see Table 3.9).

The qualitative evidence is clear that labour productivity growth is higher in ICT-intensive industries complemented by intangible capital, but what is the quantitative implication in terms of productivity growth? The mean rate of accumulation of intangible capital is four percent (see Table 3.4). Consider the difference between an industry accumulating at an annual rate of three percent and an industry accumulating at a rate of five percent, which is a difference far below the standard deviation of 0.06, this translates into a difference in labour productivity growth of 0.35 percent (0.174% $\times$ 2). If one further assumes that the industry with slow accumulation of intangibles has an ICT intensity at the lowest quartile and the other industry has an ICT intensity at the highest quartile, the difference in labour productivity growth rises to 0.677 percentage points. Comparing these results to similar considerations in Corrado et al. (2014), the following differences are noteworthy. First, after taking into account industry-specific measures of intangible investment, the average output elasticity of intangible capital at 0.174 is much lower than the 0.4–0.7 found in Corrado et al. (2014). Second, the growth differentials of labour productivity are larger than the magnitude suggested by Corrado et al. (2014).[18] These differences seem to indicate that the aggregate growth of intangibles is an imperfect proxy for industry-level growth. It tends to overstate the mean output elasticity of intangibles and understate the complementarity effect between ICT and intangible capital.

[17] For the ICT intensity measured by ICT share of total capital services, only the OLS estimation is reported. This is because the validity test of the instruments is not met. The first stage F statistic for excluded instruments has a value close to zero (F=0.02).

[18] An exact comparison of the values in this chapter with those from Corrado et al. (2014) is difficult because of different levels of aggregation. But considering both country-level accumulation of intangibles and industry-level ICT intensity at the lowest and the highest quartile, they find a differential growth effect between 0.4 and 0.5. One notable difference with the specification used in Corrado et al. (2014) is that we account for both country and industry fixed effects, while the industry fixed effect is omitted in their estimation.

Table 3.8: ALTERNATIVE MEASURES OF ICT INTENSITY

	(1)	(2)	(3)	(4)	(5)
	Share of VA		**Share of capital compensation**		**Share of capital services**
	OLS	IV	OLS	IV	OLS
$\text{NICT}_{c,i,t}$	0.305***	0.304***	0.308***	0.308***	0.365***
	(0.050)	(0.050)	(0.052)	(0.054)	(0.045)
$\text{ICT}_{c,i,t}$	0.071***	0.077***	0.077***	0.077***	0.078***
	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)
$\text{INT}_{c,i,t}$	0.160***	0.151***	0.146***	0.148***	0.123***
	(0.032)	(0.031)	(0.033)	(0.035)	(0.026)
$\text{NICT}_{c,i,t} \times D^{ICT}_{c,i}$	–0.387	–0.433	–0.462	–0.796	–0.789***
	(1.275)	(1.424)	(0.568)	(0.794)	(0.248)
$\text{ICT}_{c,i,t} \times D^{ICT}_{c,i}$	–0.475	0.082	0.036	0.084	0.087
	(0.653)	(0.802)	(0.230)	(0.281)	(0.125)
$\text{INT}_{c,i,t} \times D^{ICT}_{c,i}$	2.393***	1.895*	0.838**	0.982*	0.859***
	(0.873)	(0.990)	(0.369)	(0.505)	(0.218)
Year Dummies	Yes	Yes	Yes	Yes	Yes
N	1,320	1,320	1,320	1,320	1,320
Adjusted R^2	0.215	0.214	0.215	0.214	0.228
F statistic for excluded instruments		32.63		28.69	

Notes: Column (1)–(5) apply three alternative continuous ICT intensity measures and the interaction term in all specifications are in demeaned forms. Columns (1) and (2) calculate ICT intensity as the ratio of ICT capital compensation to total value added; columns (3) and (4) calculate ICT intensity as the ratio of ICT capital compensation to total capital compensation; and column (5) divides ICT capital services by total capital services to proxy for ICT intensity. All specifications include the country-industry specific effect. Standard errors shown in parentheses are heteroskedastic-robust to country-industry clustering. ***p<0.01, **p<0.05, *p<0.1

3

Table 3.9: Analysis with Discrete Measures of ICT Intensity

	(1)	(2)	(3)	(4)	(5)
	Average EU ICT Intensity			**U.S. ICT Intensity in 1995**	
	Median split (G)	Break (D)	Break (K)	Median split (D)	Restrictive split*
NICT_{cit}	0.275***	0.293***	0.296***	0.295***	0.262***
	(0.049)	(0.050)	(0.050)	(0.049)	(0.050)
ICT_{cit}	0.087***	0.074***	0.080***	0.070***	0.077***
	(0.028)	(0.024)	(0.026)	(0.024)	(0.028)
INT_{cit}	0.156***	0.127***	0.155***	0.160***	0.165***
	(0.036)	(0.032)	(0.035)	(0.035)	(0.037)
$\text{NICT}_{cit} \times Intensive$	–0.035	0.056	–0.076	–0.047	–0.020
	(0.100)	(0.098)	(0.102)	(0.098)	(0.099)
$\text{ICT}_{cit} \times Intensive$	0.005	–0.004	0.009	–0.036	–0.020
	(0.043)	(0.035)	(0.041)	(0.035)	(0.042)
$\text{INT}_{cit} \times Intensive$	0.116*	0.143**	0.116*	0.168**	0.159**
	(0.070)	(0.061)	(0.068)	(0.067)	(0.074)
Year Dummies	Yes	Yes	Yes	Yes	Yes
N	1,200	1,320	1,320	1,320	1,080
Adjusted R^2	0.206	0.217	0.213	0.217	0.188

Notes: Column (1) to (3) splits the industries into ICT-intensive and non-intensive groups based on the EU average ICT intensity values observed in the upper-left panel of Figure 3.1; column (1) only has a sample of 1200 observations. This is because industry G has an ICT intensity value nearly identical to the Manufacturing industry *D*. It seems inappropriate to include industry *G* as ICT intensive industry, as doing so would also mean industry *D* should be classified as ICT-intensive industry as well. On the other hand, include industry *G* as ICT non-intensive would result in an identical specification as the one shown in column (3). As a result, industry *G* does not belong to any of the groups and is intentionally omitted. Column (4) and (5) apply or combine the splitting criterion from the U.S. ICT intensity values. All specifications include the country-industry specific effect and the interaction terms are in demeaned forms. Standard errors shown in parentheses are heteroskedastic-robust to country-industry clustering. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

* Restrictive split means that only industries that are above (below) the median value of ICT intensity in both EU and U.S. rankings are considered ICT-intensive (ICT non-intensive). Manufacturing industry *D* and Wholesale and retail trade industry *G* are dropped from analysis because their ICT intensity rankings are not consistent across the EU and U.S. ICT intensity measures. As a result, the analysis only has a sample of 1,080 observations.

3.5.2 Analysis by asset types

Intangible capital is highly heterogeneous containing a wide range of distinctive asset types. To gain a deeper insight into which intangible asset is most likely to complement ICT investment, we further analyse the complementarity hypothesis for each of the six intangible assets individually.[19] According to the existing microeconomic literature, organisational structures seem most likely to complement ICT investment. The underlying theory, as argued by Brynjolfsson and Hitt (2000) and Brynjolfsson et al. (2002), is that as a 'General Purpose Technology', ICT offers the opportunity to restructure the organisation of a firm so that the firm can be more efficient by minimising

Table 3.10: Analysis by Asset Types

	(1) OC	(2) RD	(3) OC & RD	(4) All assets
$\text{NICT}_{c,i,t}$	0.338***	0.361***	0.317***	0.248***
	(0.051)	(0.054)	(0.058)	(0.071)
$\text{ICT}_{c,i,t}$	0.073***	0.067**	0.062**	0.074***
	(0.024)	(0.026)	(0.024)	(0.024)
$\text{OC}_{c,i,t}$	0.094***		0.093***	0.086***
	(0.018)		(0.018)	(0.019)
$\text{OC}_{c,i,t} \times D_{c,i}^{ICT}$	0.198**		0.205**	0.282**
	(0.087)		(0.102)	(0.132)
$\text{RD}_{c,i,t}$		0.074***	0.069***	0.059***
		(0.016)	(0.015)	(0.015)
$\text{RD}_{c,i,t} \times D_{c,i}^{ICT}$		0.341***	0.324***	0.304***
		(0.088)	(0.078)	(0.085)
Year Dummies	Yes	Yes	Yes	Yes
N	1,320	1,200	1,320	1,200
Adjusted R^2	0.206	0.206	0.223	0.239

Notes: All specifications include the country-industry fixed effect and all interaction terms are demeaned for estimation. The ICT intensity indicator used is the baseline measure calculated as the ratio of ICT capital services to labour services. Standard errors shown in parentheses are heteroskedastic-robust to country-industry clustering. The last column 'All assets' means that all seven different intangible asset types are included for estimation. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
OC: organisation capital, RD: research and development

[19] As shown in Table 3.2, seven different intangible assets are identified but the analysis of the complementarity hypothesis was only possible for six assets because data for new financial product (NFP) are only available for one industry (i.e. Financial Intermediation) while missing for others. After controlling for the country-industry specific effect, NFP drops out in estimation.

the costs of information acquisition and processing. In other words, ICT capital becomes most productive when firms have an organisational structure that really benefits from ICT adoption. Although there is a lack of theoretical underpinning, the other asset that has been tested in the literature for complementarity with ICT is investment in R&D. Few studies using firm-level company accounts data have produced mixed results. Polder et al. (2010) find a complementarity effect between investment in ICT and R&D for a sample of Dutch services firms, while Hall et al. (2013) fail to identify such an effect for Italian firms.

Using the intangible investment data by industry, this chapter is able to show that both organisation capital and R&D capital exhibit a higher output elasticity in more ICT-intensive industries (see Table 3.10). These results are robust whether only one single asset is estimated (i.e. Table 3.10, columns 1 and 2), both are considered (Table 3.10, column 3), or even all intangible assets are included for estimation (Table 3.10, column 4).

3.6 Conclusions

The discussion of intangible investment has undoubtedly gained momentum in both academia and policy-making circles. Using an industry breakdown of the INTAN-Invest data to the level of 1-digit NACE industries, we are the first to rigorously and systematically examine the potential complementarities between investment in intangible capital and ICT capital at the industry level.

This chapter offers three key findings. First, intangible capital contributes systematically to labour productivity growth and its output elasticity is found to be significantly higher in ICT-intensive industries than in those that use little ICT. This means that intangible capital deepening makes a greater contribution to growth when complemented by ICT investment. This finding supports the complementarity hypothesis proposed in prior microeconomic studies. Second, using industry-level rather than country-level data on intangibles, we find a much smaller mean output elasticity of intangible capital, but a larger differential effect of labour productivity growth across industries with varying degrees of ICT intensity. Third, not all individual intangible assets are complementary to ICT investment. In the sample of assets investigated, only organisational structures and research and development (R&D) are found to be conducive to the exploitation of ICT. While other assets, such as design or market research, are not complementary to ICT capital.

These results offer important implications. The poor productivity performance observed in Europe since the mid-1990s does not seem to be solely caused by a lower level of investment in ICT (Van Ark et al., 2008), but also by a lower level of investment in intangible capital, which led to a much less effective exploitation of ICT capital in that period.

To gauge quantitative implications, we compare an industry with an ICT intensity at the lowest quartile to an industry at the highest quartile, assuming at the same time a difference in intangible capital growth of two percentage points. Taking the estimates at the face value, these differences in inputs lead to a growth differential of labour productivity of over 0.677 percentage points. This effect is economically important, but it remains suggestive and speculative, since we fail to uncover a definite causal relationship between intangible capital accumulation and labour productivity growth. Decomposing the error term into a correlated country-industry specific fixed effect and a full set of time dummies does not satisfactorily solve the issue of simultaneity bias, since it hinges on a highly restrictive assumption that the unobservable productivity shocks are time-invariant and country-industry specific. The more structural control function approaches of Olley and Pakes (1996) and Levinsohn and Petrin (2000) are not readily applicable to data of an industry-level setting with multiple inputs. Moreover, much remains to be done to improve industry-level measurement of intangibles (e.g. with regard to appropriate price deflators and depreciation rates), where the industry intangible investment data constructed by Niebel et al. (2013) based on INTAN-Invest are still to be seen as experimental.

Despite these caveats, this study offers an important insight into the productive nature of ICT and intangible capital, the source of growth that the modern economy increasingly relies on.

CHAPTER 4

Cross-country income differences: Accounting for the role of intangible capital

4.1 Introduction

Living standards, as captured by average income per person, vary dramatically across countries. According to the estimates of the World Development Indicators (World Bank, 2015a), the ratio of 90th to 10th percentile in the world income distribution is at an alarming factor of 28 in 2012.[1] What can explain such enormous differences in income per capita across countries?

Based on the Solow growth model economists have been seeking to provide answers around two proximate determinants: differences in *factors of production* and in *efficiency*. This analytical framework is formally known as development accounting. The main idea of this analysis is that by using cross-country data on output and inputs at one single point in time, development accounting quantifies how much of the cross-country variation in income can be accounted for by the observed differences in production factors and how much is left to be explained by the differences in efficiency as measured by total factor productivity (TFP). The latter is a residual, i.e. everything that cannot be accounted for by the observable inputs.[2] The current consensus is that efficiency plays the largest role in accounting for cross-country income variation, while the observed differences in factor inputs merely account for a small share (Caselli, 2005; Easterly & Levine, 2001; Hall & Jones, 1999; Mutreje, 2014).

[1] Real GDP per capita is calculated using constant internationally comparable dollars (i.e. adjusted for differences in relative prices–PPPs).

[2] Abramovitz (1956, p.11) labelled it as "a measure of our ignorance".

The goal of this chapter is to extend the existing works on international income differences by accounting for an important factor of production that has been ignored so far – intangible capital. This is likely to be a promising extension, as the emerging research agenda on intangible investment has shown that intangible assets, such as brand equity, scientific research and development (R&D), and organisation capital, have become increasingly the more important forms of investment in the modern economy and they have escaped the statistical net (Corrado & Hulten, 2010). In the System of National Accounts (SNA), investments are broadly defined as: the acquisition of fixed assets that is undertaken specifically to enhance future production possibilities. According to the guidelines of SNA 1993 revision, this includes physical assets such as machinery, equipment and buildings as well as a limited set of intangibles, namely software, mineral exploration, and artistic originals, which we will indicate by national accounts (NA) intangibles in the remainder. In SNA 2008, the investment boundary was extended to also cover expenditures on R&D.[3] However, this still omits other important intangible assets, such as brand equity and organisation capital.

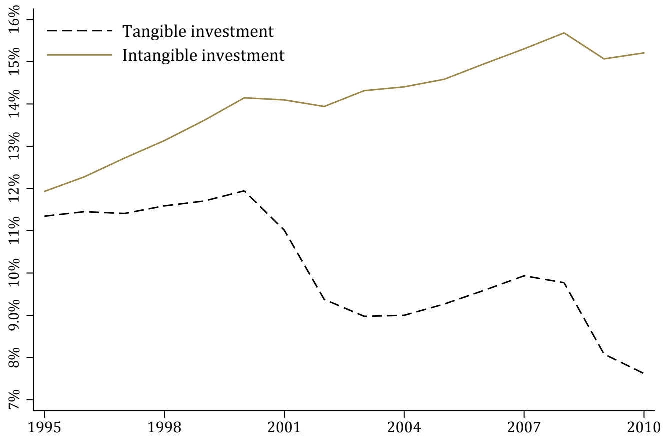
Thanks to the pioneering measurement work of intangible investment by Corrado et al. (2005, 2009), evidence is growing stronger that there is a gradual shift in investment composition towards intangible assets. In the U.S., for example, business intangible investment as a share of GDP had already exceeded the share of traditional investment in tangible assets (e.g. machinery and equipment) by the mid-1990s and has kept on rising over time (see Figure 4.1). Rather than being an exception, other country-specific studies and the research project commissioned by the OECD (2013b) also show that investment in intangibles has been rising in both high-income economies and emerging economies.[4] In light of this evidence, it is clear that the traditional emphasis on physical capital as the only capital input is missing out on an important part of investments in the modern knowledge-intensive economy. This implies that inputs might account for more of cross-country income differences than generally known so far.

This study is the first to explicitly account for a country's (business) investment in intangible capital as an additional production factor in accounting for income variation across countries. We first develop a novel database on intangible investment that is consistent and internationally comparable for a set of 60 economies over the period 1995-2011. The dataset, by itself, is a contribution to the rapidly growing literature on

[3]Since 2013 a small number of countries have started to capitalise R&D spending as investment (e.g. USA, Australia) following the guidelines of SNA 2008. Most countries around the world, however, have not yet switched to SNA 2008. For this reason, R&D is still counted as *new intangibles* instead of *NA intangibles* in this chapter.

[4]Other country-specific studies include Australia (Barnes, 2009), Brazil (Dutz, Kannebley, Scarpelli & Sharma, 2012), China (Hulten & Hao, 2008), South Korea (Chun, Fukao, Hisa & Miyagawa, 2012), and Japan (Fukao et al., 2009).

Figure 4.1: Intangible Investment Trend in the U.S. (% of GDP)



Note: Author's calculation based on the INTAN-Invest database

intangible investment as this is the first database providing internationally comparable data on intangibles for such a wide range of countries, including not only the advanced economies, but also major emerging economies like China and Brazil as well as much less developed countries, such as Honduras and Vietnam. This dataset offers two important insights. First, there is a strong positive association between the level of economic development of a country and its investment intensity in intangibles, reaffirming the important role of intangible capital in modern economic growth. Second, the share of investment in intangible assets as a percentage of (intangibles-adjusted) GDP has been increasing steadily over time, while the share of traditional investment in physical assets is highly volatile and had declined somewhat during the period of observation.

4

Starting with the basic development accounting framework that features physical and human capital akin to Caselli (2005), we find that the observed differences in the traditional factors of production account for approximately 23 percent of the cross-country income variation in 2011. This result holds true whether the analysis is based on the total economy or the market economy which excludes public sectors such as Public Administration and Defence. Therefore, for the set of 60 economies that we cover efficiency is still the main factor accounting for international income differences, conforming to the findings of the existing literature (e.g. Caselli, 2005; Easterly & Levine, 2001; Mutreje, 2014). In the augmented development accounting analysis where intangible capital is included as an additional factor of production, we show that the variance accounted for by the observed differences in inputs increases significantly and systematically across a wide range of specifications. Depending on the assumptions regarding the output elasticity of intangible capital, the observed differences in factor inputs can account for up to 40 percent of the income variation, an improvement of 16 percentage points compared to the conventional analysis that ignores intangible capital. Even under a more conservative specification, we still find that including intangible capital leads to an increase of nearly 5 percentage points of income variation.

Before proceeding, it is helpful to place these results in a broader context. The emphasis on the comparability of the intangible investment series across a set of 60 economies has required rather restrictive assumptions that apply to all countries and measuring intangible investment in a less comprehensive fashion. For instance, we have only focused on three major intangible assets that can be well covered using standardised international databases, which leaves out intangible investment in, for example, firm-specific human capital. This means that the estimates constructed in this study do not reflect the full extent of intangible investment. Superior in this regard are the outcomes of the INTAN-Invest project (Corrado et al., 2012) and other country-specific studies that mainly rely on national accounts and national survey data to measure intangible investment.[5] However, since such studies have not achieved the level of country coverage necessary for an informative development accounting exercise, we have developed our estimates specifically for this purpose.

A key finding of this chapter is that intangible capital is important in accounting for cross-country income variation at a single point in time. This echoes with the macro-level studies that find intangible capital to be important for a country's growth over time (e.g. Corrado et al., 2009; Dutz et al., 2012; Fukao et al., 2009). In both cases, the role of efficiency, measured by TFP, is diminished once intangible capital is accounted for.

Since our analysis is an accounting exercise, it can shed no light on whether investing more in intangible assets would lead to higher income or if causality runs the other way. However, there are prior firm-level studies that analyse the role of intangible capital in determining firm productivity and performance. For instance, using a large panel of company accounts data, organisation capital is found to lead to higher firm productivity (Chen & Inklaar, 2016; Tronconi & Vittucci Marzetti, 2011) and larger stock market returns (Eisfeldt & Papanikolaou, 2013), and it is also complementary to the exploitation of the productivity potentials of information technologies (Bloom et al., 2012; Brynjolfsson & Hitt, 2000, 2003). At the firm level, there thus seems to be a causal relationship between investment in intangibles and productivity. One of the main insights from our analysis is that high-income countries tend to invest more in intangibles than lower-income countries, which raises the question why firms

[5]See footnote 4 for the list of country-specific studies.

in lower-income countries are not investing more. So far, the evidence on this is scarce, though Bloom, Eifert, Mahajan, McKenzie and Roberts (2013) find that the adoption in Indian manufacturing firms of modern management practices – a form of investment in organisation capital – is hampered by informational barriers. While it is a useful piece of evidence, this is a question that awaits further research.

The rest of the chapter is organised as follows. Section 4.2 describes the general measurement procedure of intangible investment and how capitalising expenditures on intangible assets changes the conventional gross domestic product (GDP) concept. A brief discussion on the key features of the intangible investment data is presented in the second part of Section 4.2. Section 4.3 outlines the basic and the augmented development accounting framework and elaborates on the data that we use for analysis. Results, obtained across various specifications, and robustness checks are discussed in Section 4.4. Section 4.5 concludes and discusses the main limitations of this study.

4.2 Measuring intangible inputs and output

In this section we describe the general approach used to measure intangible investment and show how capitalising such investment requires a change in the measurement of GDP. Then, we discuss the list of intangible assets measured in this study as well as the key features of the data that we construct and use for the subsequent development accounting analysis. It is important to note that this section only provides a general overview of the measurement procedure. For a more extensive and detailed discussion on the data construction of intangibles, please refer to Appendix 4.A.

4.2.1 General measurement approach

Before discussing how to measure intangible investment, a natural question to ask a priori is: why do we need to reclassify expenditures on intangibles and capitalise them as investment? The argument is presented more formally in Corrado et al. (2005) based on inter-temporal capital theory, but the simple answer is: "*any* use of resources that reduce current consumption and production in order to increase it in the future" should be capitalised as investment. Expenditures on tangible assets, such as office buildings, machinery, vehicles, and equipment certainly satisfy this criterion, but so does much spending on brand equity, R&D, and organisational structures.[6] Expenditures on these

[6]R&D projects, for instance, can take more than a decade to generate revenue and require large co-investments in marketing.

assets, collectively termed new intangibles in this chapter, contribute to (rather than detract from) the value of individual companies and growth of the economy.

While few would disagree with the potentially long-lasting benefits of intangible capital and their role as productive inputs, little is known about the size of intangible investment at the level of the economy.[7] The measurement of intangibles is particularly difficult as they are often created for internal use within the firm and suffer from a lack of observable market transaction data for valuation. To circumvent this measurement issue, researchers turned to use the cost approach as an alternative. The underlying assumption of the cost approach is that firms are willing to invest in intangible assets until the discounted present value of the expected income stream equals the cost of producing the marginal asset (Jorgenson, 1963).

A key problem of this cost approach, however, is that it is not known with precision how much or what portion of intangible spending has long-lasting impact (i.e. longer than one year) and can be and should be treated as investment. In this chapter, we follow the work of Corrado et al. (2005) which suggests a wide range depending on the specific asset. For own-account organisation capital, 20 percent of managers' wage are counted as conducive to organisational development; for advertising, the literature suggests that about 60 percent of advertising expenditures have long-lasting benefit. While for R&D all expenses are treated as investment following SNA 2008.

To cumulate intangible investment flows (N) into capital stocks, one can use the usual perpetual inventory method (PIM) which accumulates past capital formation and subtracts the value of assets due to obsolescence. Physical capital is generally subject to value loss because they tend to be used up in production mainly due to wear and tear. Intangible capital, on the other hand, does not physically deteriorate due to its intangibility. It is more subject to the rise of superior knowledge that supplants the existing ones and thereby making the current intangible or knowledge stock obsolete.

By including some expenditures as investment, one also needs to adjust the GDP concept. More specifically, a country's nominal GDP as measured traditionally (Y) will be expanded accordingly as follows:

$$GDP' \equiv Y + N = \overbrace{C + I + \underbrace{N}_{added}}^{\text{Expenditure side (GDP)}} = \overbrace{L + K + \underbrace{R}_{added}}^{\text{income side (GDP)}} \tag{4.1}$$

[7] Various proxy measures, such as business surveys, are used in firm-level studies (e.g. Black & Lynch, 2005; Lev & Radhakrishnan, 2005).But none of these proposed approaches yield the kind of comprehensive measure needed for national accounting or source-of-growth analysis.

where N is the flow of new intangible investment added on to the expenditure side and R is the income from the flow of services provided by the intangible capital stock. In other words, intangible capital is now both a productive input (R) and a part of intangibles-augmented output (N). This new concept of GDP, denoted by GDP', is larger in magnitude than conventionally defined.

4.2.2 List of intangibles measured and overview of the data

We assemble internationally comparable data to estimate intangible investment for a set of 60 economies over the period 1995-2011 (see Appendix Table 4.A1 for the full list of economies covered). We capture the following three intangible assets in this study: brand equity, R&D, and organisation capital. Brand equity can be seen as the value premium that a firm can capitalise on from a product or service with a recognisable name as compared to its generic equivalent. Following Corrado and Hao (2014), we measure brand equity as the sum of expenditures on advertising and market research. R&D refers to the innovative activities leading mainly to the development of a new or improved product and it is measured by business expenditures on R&D. Organisation capital can be thought of management know-how and the information a firm about its assets and how these can be used in production (Prescott & Visscher, 1980). Following the broad literature, organisation capital is measured as a fraction of manager's wage compensation. Table 4.1 provides a general overview of the list of intangibles covered, how they are measured, and the sources of the data used. Readers should refer to Appendix for more detailed discussions on the measurement issues.

Table 4.1: List of Intangible Assets Measured and Data Sources

Asset Type	**Measured by**	δ	**Data source***
Brand equity	Spending on advertising and market research	60%	WARC & ESOMAR
Scientific R&D	Business expenditures on R&D	20%	UNESCO & Eurostat
Organisation capital	Wage compensation of managers	40%	ILO, PWT8.1, BLS

δ: Asset-specific depreciation taken from Corrado et al. (2009).

* ILO: International Labour Organisation; PWT: The Penn World Table version 8.1; BLS: Bureau of Labour Statistics; WARC: World Advertising Research Centre; ESOMAR: European Society for Opinion and Marketing Research; UNESCO-UIS: UNESCO Institute for Statistics; Eurostat: Statistical Office of the European Communities.

It is important to emphasise that these do not include all intangible investments in the economy. As noted earlier, investment in national accounts intangibles are already capitalised and included in investment and GDP statistics following the SNA 1993.

There is hence no need for additional estimation.[8] Corrado et al. (2005) include three other intangibles, namely architectural and engineering designs, firm-specific human capital, and new financial products, but these are relatively minor. According to the estimates of the INTAN-Invest project, a pioneering database providing country-level intangible investment data for a sample of 29 countries, the sum of these three assets account for nearly 75 percent of the total intangible investment not covered in SNA 1993 statistics. Thus, in terms of their shares in total intangible investment these three assets can be considered as the most important ones to capture.

Like many other studies on intangibles, we focus on market sector investment in intangible assets and omit public intangible investment due to measurement difficulties.[9] Hence, a country's market GDP (MGDP) after adjusting for business investment in intangible assets is calculated as follows:

$$MGDP'_{c,t} \equiv mY_{c,t} + N^{BE}_{c,t} + N^{RD}_{c,t} + N^{OC}_{c,t} \tag{4.2}$$

where m denotes the share of market economy; Y denotes GDP calculations based on SNA 1993 revision, and intangible investments are represented by the letter N indexed by the asset-specific superscripts – BE, RD, and OC.

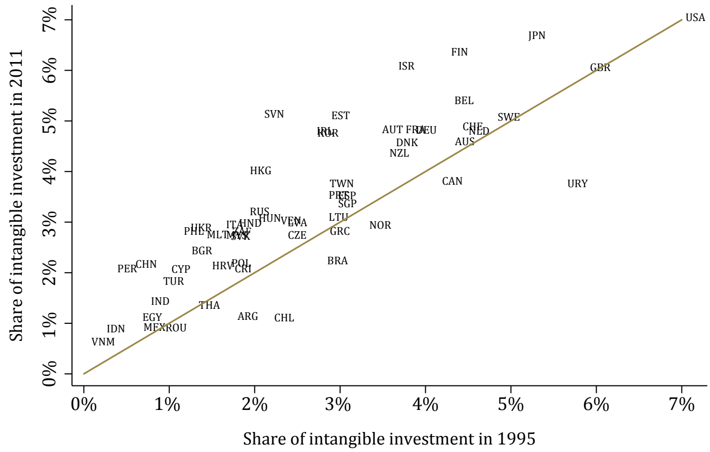
The intangibles data constructed in this study offers several important insights. The first is that, there has been a steady increase in the share of investment in intangibles between 1995 and 2011 for most of the countries covered in our sample (see Figures 4.2 and 4.3). Whereas, the same is not true about the share of traditional investment in physical assets, which had declined somewhat over time. These two contrasting investment trends or patterns seem to suggest that the modern economy is currently undergoing structural changes with investment composition shifting gradually towards intangible assets.

In addition, it is also interesting to note the difference in volatility of investment in tangible and intangible assets. Figure 4.3 shows that investment in intangible assets as a share of MGDP′ seems to be much more stable and resilient to economic downturns, while traditional investment in tangible assets appears to be highly volatile and sensitive to external shocks. This is reflected by the sharp decline in tangible investment share observed in 1997, 2001, and 2008. In chronological order, these three years are,

[8] To have a full-fledged analysis on how the addition of total intangible capital affects the development accounting analysis, it would be ideal to isolate those national accounts intangible investments from total tangible investment (I) and reclassify them as intangibles. This is however not possible due to data constraints.

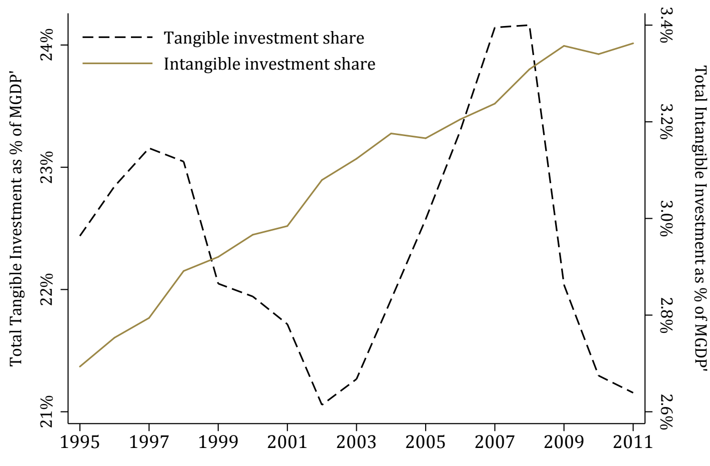
[9] The distinction between market and nonmarket (public) sector is the same as defined in EU KLEM (O'Mahony & Timmer, 2009). According to NACE classification, sectors A-K plus sectors O and P consist of market sector. See Appendix 4.B for more detailed discussions.

Figure 4.2: Intangible Investment as a Share of MGDP′ in 1995 and 2011



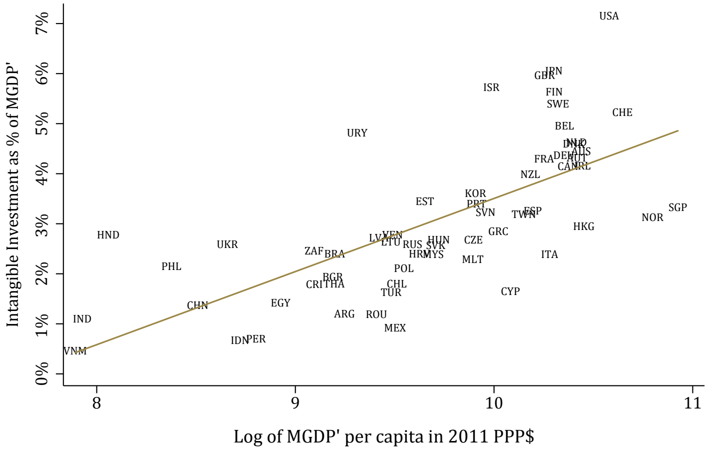
Notes: Author's calculation. The line shown in the figure is a 45 degree line. Both axises denote intangible investment as a share of MGDP', one for 2011 and the other for 1995.

Figure 4.3: Cross-country Average Investment Trend of Intangibles and Tangibles



Notes: Author's calculation. The shares of tangible and intangible investments are averaged across countries.

Figure 4.4: Intangible Investment and Level of Economic Development



Notes: Author's calculation. The line shown in the figure is OLS regression line. The shares of intangible investment are averaged over time.

respectively, associated with the Asian financial crisis, the dot-come bubble burst, and the global financial crisis.

Third, the world's leading investor in intangible capital is the U.S., which has an average intangible investment share of over 7 percent of MGDP′. Vietnam, on the other hand, has the smallest share (i.e. slightly over 0.5% of MGDP′). The positive slop of the fitted line shown in Figure 4.4 suggests that there is a strong positive correlation between the level of economic development of a country and its investment intensity in intangible assets, which is above 0.67. This, of course, could mean that rich countries tend to invest more in intangible assets or that, intangible assets tend to make these investing countries richer.

4.3 Development accounting and data analysis

In this section, we revisit the basic development accounting technique and set the stage for the extension of the basic model, which already features physical capital and human capital as factor inputs, to further include intangible capital. Then, we elaborate on the data that we use for the development accounting analysis and briefly discuss how the key variables of interest are constructed.

4.3.1 Development accounting framework

The point of departure for our empirical analysis is the benchmark Hall and Jones (1999)'s production function:

$$Y = A \cdot K^{\alpha} \, (Lh)^{\gamma} \tag{4.3}$$

where Y is a country's GDP, K is the aggregate physical capital stock and Lh is employment adjusted for labour quality (i.e. number of workers L multiplied by their average human capital h). The superscripts α and γ are the output elasticities of capital and labour,[10] and A denotes the state of technology with which production factors are combined to produce output. Assuming that the production function features the property of constant returns to scale (i.e. $\gamma = 1 - \alpha$) and normalise the function by the number of employees, equation (4.3) can be rewritten as follows:

$$y = A \cdot k^{\alpha} h^{1-\alpha} \tag{4.4}$$

where y is the output per worker, k is the capital-labour ratio for physical assets (i.e. K/L). Equation (4.4) basically asks how much of the variation in output per worker y can be attributed to variation observed in physical capital k and human capital h, each weighted by their output elasticities, and how much is left to be accounted for by differences in technology A or total factor productivity (TFP).

Akin to Caselli (2005), we define $y_{KH} \equiv k^{\alpha} h^{1-\alpha}$ as the so-called factor-only model and for ease of exposition rewrite equation (4.4) accordingly as:

4

$$y = A \cdot y_{KH} \tag{4.5}$$

where both y and y_{KH} are observable. In the tradition of variance decomposition, this equation can be further transformed as follows:

$$var[log(y)] = var[log(A)] + var[log(y_{KH})] + 2cov[log(A), log(y_{KH})] \tag{4.6}$$

The explanatory power of observed input differences is then defined as:

$$\text{VAF} = \frac{var[log(y_{KH})]}{var[log(y)]} \tag{4.7}$$

where VAF denotes the fraction of income variances accounted for by the observed differences in factor inputs. The higher the value of VAF, the higher the explanatory

[10] In growth or development accounting the output elasticity of factor inputs is equal to its income share if inputs earn their marginal product and firms maximise profits. We will speak of output elasticities, instead of income shares, throughout this chapter.

power of the observable inputs. In the work of Caselli (2005), this ratio or fraction is alternatively labelled as the success rate: how successful are observable factor inputs in accounting for cross-country income differences?

We extend the basic framework to further include intangible capital (R) as an additional production factor and denote its output elasticity by a constant parameter β. Then, the augmented production function in per worker terms becomes:

$$y\prime = A \cdot y_{KRH} = A \cdot k^{\alpha} r^{\beta} (h)^{1-\alpha-\beta} \tag{4.8}$$

where $y_{KRH} \equiv k^{\alpha} r^{\beta} h^{1-\alpha-\beta}$ denotes the *augmented* factor-only model; the superscripts α and β represent the output elasticities for tangibles and intangibles; and $y\prime$ is the market GDP adjusted to include intangible capital constructed per equation (4.2). Again, following Caselli (2005) the decomposition of the variation in GDP per worker is now given by:

$$\text{VAF}' = \frac{var[log(y_{KRH})]}{var[log(y\prime)]} \tag{4.9}$$

The prime interest is essentially the difference between VAF and VAF′. If intangible capital is important in accounting for international income differences, one would expect the value of the latter to exceed the former. In fact, the larger the difference between the two ratios, the larger the role of intangible capital in accounting for income variation.

4.3.2 Basic data

The basic data we use are obtained from various sources. Countries' (nominal) GDP and total investment in tangible assets,[11] and number of workers are primarily extracted from the United Nations National Accounts (UN NA) database, human capital (h) comes from the standard database of Barro and Lee (2013), and total investment in intangibles (N) is constructed in this study. Since both GDP and investment are denominated in local currency unit (LCU) and are expressed in nominal terms, we first estimate real GDP per worker ($RGDPWOK_{c,t}$) and real value of tangible investment ($I_{c,t}$) in international comparable dollars as follows:

$$y_{c,t} \equiv RGDPWOK_{c,t} = GDP_{c,t}/P_{c,t}/ppp_{c,2011}/emp_{c,t} \tag{4.10}$$

$$I_{c,t} = GFCF_{c,t}/P^{I}_{c,t}/ppp_{c,2011} \tag{4.11}$$

[11]Investment is measured by gross fixed capital formation (GFCF). Since Taiwan is not covered in the UN NA database, we alternatively extract its (nominal) GDP and total gross fixed capital formation (I) from the PWT 8.1 database.

where the subscripts c and t denote country and year, respectively; P is the GDP price deflator with 2011 as base and ppp is the GDP PPP divided by the exchange rate in 2011 and is taken from the World Development Indicators (World Bank, 2015a). Physical capital stock K is calculated using the perpetual inventory method:[12]

$$K_{c,t} = I_{c,t} + (1 - \delta_K) \cdot K_{c,t-1} \tag{4.12}$$

where I is the real investment in traditional tangible assets deflated by the investment price deflator (P^I) and δ_K is the rate of depreciation for physical capital K, which is set equal to 0.06 following the broader literature (e.g. Caselli, 2005).[13] For the initial capital stock calculation (K_0), we follow the standard approach proposed by Harberger (1978) by assuming the steady-state relationship from the Solow growth model:

$$K_0 = I_0/(g + \delta_K) \tag{4.13}$$

The initial capital stock K_0 for an asset is related to investment in the initial year I_0, the (steady-state) growth rate of investment g and the rate of depreciation δ. Unlike intangible investment data that is only available for 17 years (i.e. 1995-2011), tangible investment I is, for many countries, available since 1960.[14] Therefore, to make the best use of the existing data, tangible capital stock K is constructed for a much longer time series than intangible capital stock, which we turn to discuss in the next subsection.[15] The (physical) capital-labour ratio is calculated as:

$$k_{c,t} = K_{c,t}/emp^{PWT}_{c,t} \tag{4.14}$$

4

[12]It would be ideal to measure capital services rather than capital stocks as a capital input measure, as a capital services measure would capture the larger return of shorter-lived assets. However, the data requirements are much more demanding for estimating capital services than for capital stock and there is no readily available data to measure capital services. For instance, one would need additional information on the user cost of capital to calculate capital services. The user cost of capital requires the rate of return on capital and the rate of asset-specific inflation. The former is generally hard to measure with precision (e.g. Inklaar, 2010) and data on the asset-specific capital gains are not available for many countries. Due to these practical constraints, total capital stock (both tangible and intangible) based on perpetual inventory method is used as a measure of capital input, rather than the preferred services measure. Note, the existing studies on international income differences generally relied on a stock measure as well for capital input (e.g. Caselli, 2005; Mutreje, 2014), so the results obtained in this chapter by adding intangibles as an additional capital input can be directly compared to previous studies.

[13]The investment price deflator for tangible assets P^I is calculated as GFCF at current national prices divided by GFCF at constant national prices. Both data series are retrieved from the UN NA database.

[14]To be precise, 1960 (29 countries), 1965 (2 countries), 1966 (1 country), 1968 (1 country), 1970 (18 countries), 1980 (1 country), 1989 (2 countries), 1990 (6 countries).

[15]With a rate of depreciation of 6%, a much longer time series is also needed to calculate tangible capital stock, especially for the initial capital stock. To note, there are nine East European countries that do not have a reasonably long time series of tangible investment (i.e. dating back to 1970), we will drop them in the subsequent development accounting analysis for robustness check. For countries that have a negative average growth rate, we reset it to 4%, which is the mean geometric growth rate observed for the other countries.

As for human capital h, we rely on the recently updated data on educational attainment for population aged 25 and over from Barro and Lee (2013)[16]. Following the broader literature, we measure human capital h of country c at time t as a function of average years of schooling (s) as follows:

$$h = e^{\phi(s)} \tag{4.15}$$

The function $\phi(s)$ from equation (4.15) takes the following form as in earlier studies (e.g. Caselli, 2005; Inklaar & Timmer, 2013). The rationale for this form is that early years of schooling is believed to have a higher rate of return than later years. This assumption is also empirically supported by the cross-country Mincerian wage regressions (Mincer, 1974). To be precise, $\phi(s)$ is piece-wise linear with rates of return based on Psacharopoulos (1994):

$$\phi(s) = \begin{cases} 0.134 \cdot s & \text{if } s \leq 4 \\ 0.134 \cdot 4 + 0.101 \cdot (s-4) & \text{if } 4 < \text{s} \leq 8 \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068 \cdot (s-8) & \text{if } s > 8 \end{cases} \tag{4.16}$$

Unlike the basic data discussed in the previous section where y and k are calculated both for the total economy and for the market economy,[17] data on intangibles is solely constructed for the market economy. The real value of market investment in intangibles n, expressed in international comparable dollars, is computed as follows:

$$n_{j,c,t} = N_{j,c,t}/P^N_{j,c,t}/ppp_{c,2011} \tag{4.17}$$

where N denotes nominal intangible investment flows; P^N is the asset-specific price deflator for intangibles and is imputed based on the U.S. data (see Section 4.3.3 for more detailed discussions on intangible price deflator); *ppp* is the GDP PPP divided by the exchange rate in 2011 taken from WDI. Intangible capital R is then calculated using PIM:

$$R_{j,c,t} = (1-\delta^R_j) \cdot R_{j,c,t-1} + n_{j,c,t} \tag{4.18}$$

where δ^R is the country-time-invariant depreciation rate for asset j from Table 4.1. The initial capital stock is computed based on the steady-state assumption:

[16]The educational attainment data provided by Barro and Lee (2013) is available every five years, going back to 1950 and most recently up to 2010. For 2011, we assume that 2010 average years of schooling prevail.

[17]Due to the lack of data, human capital h is only calculated for the total economy and is assumed to be the same for the market economy.

$$R_{j,0} = n_{j,0}/(g_j + \delta_j^R) \tag{4.19}$$

where $n_{j,0}$ is the real value of intangible investment in 1995, and g is the average growth rate of the intangible investment series between 1995 and 2011. Given the relatively high rates of depreciation assumed for intangible capital, a time span of 17 years is long enough for the initial capital stock to have only little impact on the development accounting analysis as the true value of the initial stock will be depreciated by 2011, the year we use for cross-country analysis.[18] Intangible capital-labour ratio is computed as follows:

$$r_{c,t} = \left(R_{c,t}^{BE} + R_{c,t}^{OC} + R_{c,t}^{RD}\right) / \left(s_{c,t}^{M} \cdot emp_{c,t}^{PWT}\right) \tag{4.20}$$

where $s_{c,t}^M$ denotes the share of employment in the market sector (see Appendix 4.B2 for a more detailed discussion).

Table 4.2: Descriptive Statistics of the Basic Data for 2011 (Market Economy)

	Description	**Min.**	**Mean**	**Max.**	**S.D.**	**N**
$y\prime$	real market output per worker	7,666 (VNM)	65,747	139,955 (SGP)	33,430	60
k	physical capital per worker	15,485 (VNM)	126,681	233,007 (NOR)	63,191	60
r	intangible capital per worker	77 (VNM)	7,429	26,839 (USA)	6,731	60
h	human capital per worker	1.97 (IND)	3.00	3.70 (USA)	0.435	60

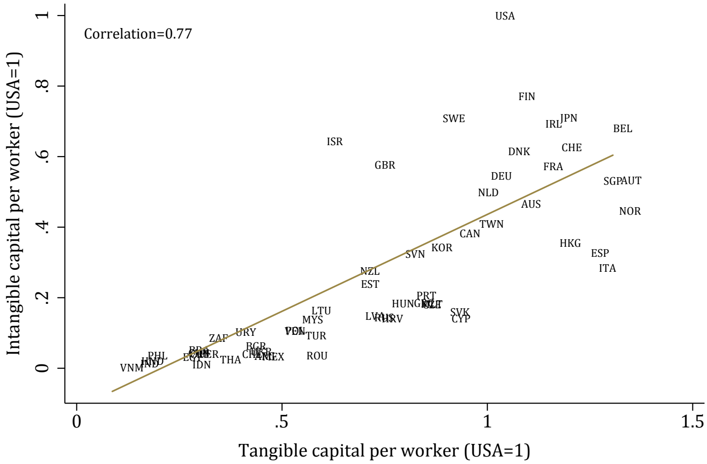
Notes: All the numbers presented in the table are based on the market-sector of the economy and only for year 2011.

To have a general overview of the data, a brief summary of some descriptive statistics is provided in Table 4.2. As can be seen, Vietnam is the poorest country in the sample with the least amount of physical and intangible capital, while Singapore has the highest income per worker. The U.S. has the highest level of both intangible capital and human capital. Figure 4.5 correlates tangible capital per worker with intangible capital per worker, both of which are normalised relative to the U.S. values. As can be seen, these

[18]Even for asset with the lowest rate of depreciation (e.g. $R^{RD} = 20\%$), the initial capital stock would wear out almost completely after 17 years: $(1-0.2)^{17} = 0.02$. This still holds true if the depreciation rate is just 15%: $(1-0.15)^{17} = 0.06$. Thus, a time span of 17 years is already long enough to measure intangible capital stock with precision.

two capital-labour ratios are highly correlated (correlation coefficient is approximately 0.77). This suggests that countries with higher tangible capital per worker tend to have more intangible capital per worker as well.

Figure 4.5: Correlation between Tangible and Intangible Capital per Worker



Notes: Author's calculation. The line shown in the figure is OLS regression line.

4.3.3 Intangible investment price deflator

Currently, there is very limited knowledge on the appropriate price measures of intangible investment as these assets tend to be internally generated and lack observable market data for valuation. The existing studies have primarily relied on the non-farm business output price deflator as a proxy for the price of intangibles and applied this deflator uniformly to all intangible assets (Corrado et al., 2012, 2009). It could be argued however that rather than using the uniform business output price deflator, more appropriate asset-specific deflators would be the price indices of the industries that produce (in part) intangible assets, such as management consulting industry for organisation capital, advertising and marketing research industry for brand equity, and R&D services industry for R&D.

Since price deflators for intangible-producing industries are not widely available for the other economies, we use the U.S., where the data are available, as the benchmark country and impute the asset- and country-specific intangible price deflators as follows:

$$R^N_{j,t,US} = P^N_{j,t,US}/P^I_{t,US} \tag{4.21}$$

where R^N denotes the relative intangible price deflator of the U.S., $P^N_{j,t,US}$ is the price deflator of the asset-specific intangible-producing industry obtained from U.S. Bureau of Economic Analysis, and $P^I_{t,US}$ is the tangible investment price deflator provided by the UN NA data. Assuming that the relative price between intangible and tangible investments are constant across countries, we derive intangible investment price for the other economies as follows:

$$P^N_{j,c,t} = P^I_{c,t} \times R^N_{j,t,US} \tag{4.22}$$

It is important to emphasise that the price of intangibles calculated per equation (4.22) is only a crude proxy and a practical choice needs to be made. Robustness to the choice of intangible price deflator, rate of depreciation of intangible capital stock, and other assumptions made during the data construction process will be examined in the next section.

4.4 Empirical results

In this section, we discuss the main empirical findings, first with results of the basic development accounting analysis which only features physical and human capital, followed by the analysis augmented to include intangible capital as an additional factor of production. By varying the output elasticities of factor inputs, we compare and contrast the findings across various specifications and discuss the robustness of the main result.

4.4.1 Basic development accounting analysis

With data on y, k and h, and setting the output elasticity of physical capital α equal to 1/3 as suggested by the broader literature, the variance of the basic factor-only model for year 2011, $var[log(y_{KH})]$, is 0.088 and the observed actual output variance, $var[log(y)]$ is 0.387 (see the first row of Table 4.3). This result suggests that, for a sample of 60 economies, only about 23 percent of the income variances can be accounted for by the observed differences in factor inputs. This fraction remains largely unchanged if we drop those nine former Soviet Union countries that do not have a sufficiently long tangible investment series going back to 1970.[19]

[19]The rationale for this sensitivity check is that for those countries that have a short investment series, the initial capital stock (calculated based on the steady-state assumption) has a non-trivial impact on the development accounting analysis because about 14 percent (i.e. 1980-2011, $(1-0.06)^{32}$) to over 25 percent (i.e. 1990-2011,$(1-0.06)^{22}$) of the initial capital stock is still in use in 2011. Only for countries

Table 4.3: Variance Accounted For: Basic Model for 2011

	Coverage	**var[log(y)]**	**var[log($\mathbf{y_{KH}}$)]**	**VAF**
Own data	Total Economy (60)	0.387	0.088	22.7%
Own data (excl. former USSR)	Total Economy (51)	0.432	0.101	23.4%
Data from PWT 8.1	Total Economy (60)	0.452	0.109	24.1%
Own data	Market Economy (60)	0.432	0.101	23.3%

Notes: Market economy indicates that the analysis is based on market– GDP, –investment, and –unemployment. The share of variance accounted for in the last column is calculated based on values to the seventh decimal point. For brevity, variance values to the third decimal point are shown in the table.

To check whether this result is plausible, we compute the VAF of the basic factor-only model by solely using the PWT8.1 data constructed by Feenstra, Inklaar and Timmer (2015) for 2011 (see Table 4.4 for the variables used). The counterfactual variance using PWT8.1 data, $var[log(y_{KH})]$ takes the value 0.109 and the observed variance of $var[log(y)]$ is 0.452, resulting in a fraction of 24 percent of the income variances accounted for by factor inputs. This rate is very similar to the prior finding. If we narrow the focus down to the market sector of the economy (i.e. y is the market output per worker, k is the capital stock accumulated by the market sector, and L is the market share of employment), the variance accounted for remains nearly identical (about 23%). So regardless of the coverage of the economy (i.e. market or total), in the basic factor-only model the differences of the observed factor inputs can account for no more than 25 percent of cross-country income differences and the rest is attributable to the differences in efficiency measured by TFP.

Table 4.4: Alternative Data from PWT 8.1

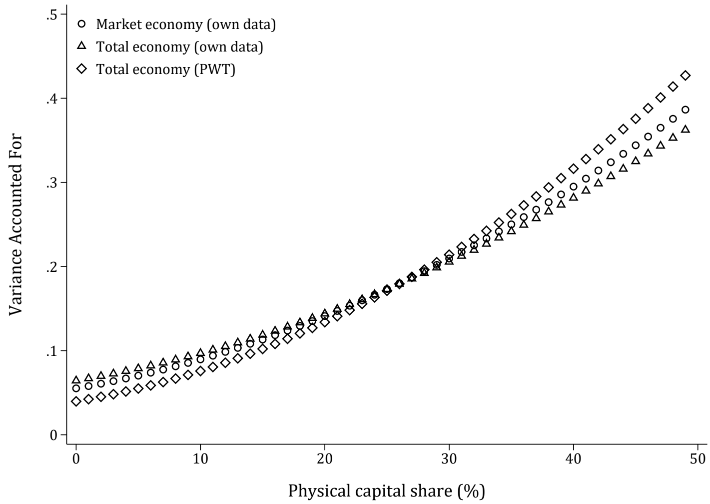
	Variables names	**Data**	**Description**
y	real output per worker	rgdpe	Expenditure-side real GDP at chained PPPs (in 2005 US$)
k	capital-labour ratio	ck	Capital stock at current PPPs (in 2005 US$)
L	number of workers	emp	Number of persons engaged (in millions)
h	human capital	hc	Human capital index, based on years of schooling

A caveat to bear in mind is that these results rest on the restrictive assumption that the output elasticity of physical capital is time-invariant and constant at 1/3. According to various recent studies (e.g. Inklaar & Timmer, 2013; Karabarbounis & Neiman, 2014;

with a reasonably long investment series (i.e. time span of 42 years or more), would the true value of the initial capital stock be (nearly) depreciated away by 2011.

Rodriguez & Jayadev, 2010), there is robust evidence that the labour share of income has been declining over time around the world. Under the assumption of constant returns to scale, this means that the income share of capital is increasing and income shares are typically used to approximate output elasticities. As a consequence, using 1/3 as the output elasticity for capital is a simplification which may not reflect the reality. Figure 4.6 plots the change of VAF as a function of the output elasticity of capital α. This analysis illustrates that as long as the output elasticity of capital is less than 50 percent (i.e. $\alpha \leq 0.5$), most of the variation in income is still accounted for by TFP. It is also reassuring that the variance accounted for remains fairly similar across different data sources and coverage of the economy.

Figure 4.6: VAF BY VARYING OUTPUT ELASTICITY OF PHYSICAL CAPITAL



4.4.2 Augmented development accounting analysis

To examine how much of the income variation can be accounted for by intangible capital, we now turn to examine the augmented factor-only model. The first challenge is to pin down the output elasticity of intangible capital β and the resulting changes of output elasticities brought to labour γ and physical capital α.[20] In a growth accounting framework, Corrado et al. (2009) find that after capitalising intangible investment in the U.S., the total capital share of income (i.e. sK + sR) rises to 40 percent, of which about 62.5 percent accrues to physical capital and 37.5 percent accrues to intangible

[20]After capitalising intangible investment, labour's share of income changes from $s_L = (P^L L)/(P^L L + P^K K)$ to $s_L = (P^L L)/(P^L L + P^K K + P^R R)$

capital (i.e. α'=0.25 and β=0.15), and the labour share of income drops to 60 percent.[21] We take these shares as the baseline but also as the upper-bound specification for the development accounting analysis. Given that the U.S. invests most intensively in intangibles assets, it is unlikely for the other economies to have an income share of intangible capital to be higher than the share of the U.S.

As shown in Table 4.5, the counterfactual variance, $var[log(y_{KRH})]$ under the upper-bound specification, takes the value 0.177 and the market output variance $var[log(y')]$ becomes 0.445. This leads to a significant improvement in the variance accounted for from 23 percent under the basic development accounting analysis to nearly 40 percent. Even if we calibrate the model to a more conservative specification with the output elasticity of physical capital unchanged (i.e. α=1/3 as previously used) and the output elasticity of intangibles accounting for merely 5 percent (i.e. β=0.05), the VAF′ ratio still has a sizable increase of about 5 percentage points as compared to the basic model that ignores intangible capital.

Table 4.5: VAF′: Augmented Model for 2011 (Market Economy)

	Output elasticities	**var[log(y′)]**	**var[log(y_{KRH})]**	**VAF′**	**Δ**
Lower-bound	$\alpha = .33$ & $\beta = .05$	0.445	0.124	27.9%	*+5%-points*
Mid-range	$\alpha = .33$ & $\beta = .10$	0.445	0.166	37.2%	*+14%-points*
Upper-bound (Baseline)	$\alpha = .25$ & $\beta = .15$	0.445	0.177	39.8%	*+16%-points*

Δ: denotes the difference in the explanatory power of the augmented model as compared to the basic model (i.e. VAF′-VAF) in percentage points.

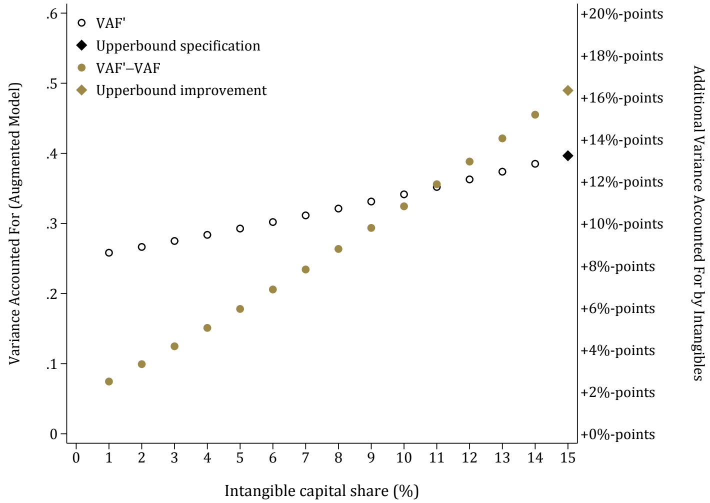
It is clear that the exact value of VAF′ is sensitive to the choice of the output elasticities. This sensitivity prevents us from drawing firm conclusions about the exact improvement of the additional variance accounted for by intangibles. The qualitative evidence, however, is clear: intangible capital systematically improves the explanatory power of observed input differences in accounting for income variation. As shown in Figure 4.7 where we keep the output elasticity of labour fixed at 60 percent (i.e. γ=0.6) and only vary the output elasticities between two capital inputs,[22] the variance accounted for is

[21] Similar pattern-changes, but in much larger magnitude, also emerged in studies that rely on econometric estimation. For a sample of EU countries, Roth and Thum (2013) find the following output elasticities for these factor inputs: α'=0.30, β=0.25, and γ'=0.45.

[22] This can be seen as the most conservative specification, as labour share has been declining over time as argued previously in the text. Thus, using 60 percent for the labour share (after adjusting for intangible capital which would also decrease labour share, see footnote 18) should be the maximum possible. Since the variation of human capital is less than the other capital inputs, changing the labour share to any value less than 60 percent would only increase VAF by factor inputs. In other words, the improvement shown in Figure 4.7 is on the conservative side.

increasing steadily as we increase the share of intangible capital (and thus decrease the share of tangible capital).

Figure 4.7: Changes in VAF by Varying Output Elasticities of Capital Inputs

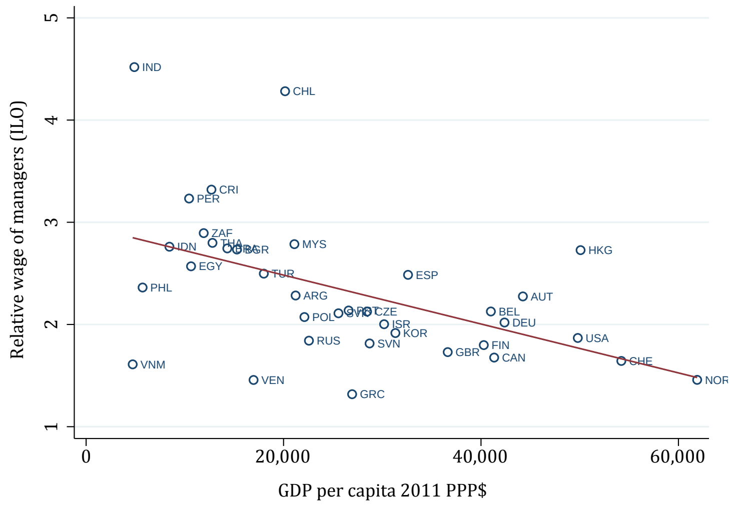


4.4.3 Robustness of the main result

Despite the fact that the quantitative implication is sensitive to the choice of the output elasticities of factor inputs, the main result is that including intangible capital systematically improves the explanatory power of observed input differences in accounting for income variation across countries. In this subsection, we test the robustness of this main result using various alternatives. The baseline is the upper-bound result from Table 4.5 (i.e. output elasticity of intangibles at 0.15). We discuss how this baseline result changes when we make alternative choices in various stages of the data construction process.

First, investment in organisation capital is measured by the wage compensation of the managers, but data on wage compensation by occupation is not widely available outside the U.S. Our main results are based on the assumption that the relative wage of managers to an average worker is the same for all the other countries as in the U.S. Based on the scant earnings data provided by the International Labour Organisation, a fairly strong negative relationship can be observed between a country's level of investment and its wage differentials (see Figure 4.8). Thus, using the U.S. relative wage would mean that we are likely to underestimate the actual level of investment in organisation capital

Figure 4.8: Relative Wage Differentials and Level of Economic Development



for most of the other economies covered in our sample, as countries at a lower level of development tend to have a larger wage differential than the benchmark economy – the U.S. In light of this evidence, we provide an alternative measure of investment in organisation capital that allows for the relative wage of managers to an average worker to differ by country (i.e. R_c).[23] As shown in the first row of Table 4.6, applying this alternative measure of organisation capital has little impact on the main result.

Second, due to data constraints, the intangible investment data of some countries have mainly relied on imputations. For instance, business investment in R&D for Brazil is approximated based on the data from Mexico (see the Appendix for greater detail). In the second and third rows of Table 4.6, we show that the main result remains unchanged to alternative country samples. It is not sensitive to dropping Spain and Greece, two countries with anomalously large amount of investment in organisation capital, or dropping Brazil, Egypt, Honduras, and Venezuela, countries with investment in R&D imputed.

[23] The alternative wage differential R_c is based on the limited earnings data by sex and occupation from the ILOSTAT database. We use the ISCO 2008 classification and retrieve the wage data for two occupational categories: Managers and Total for 2009, 2010 and 2011, the only three years that have the wage data available. In total, 35 countries are covered by ILO. Since there is little variation over time, we take an average of the ratio ($Managers/Total$) and held it constant for all years. Hence, the alternative measure of organisation capital assumes a country-variant but year-invariant wage rate for managers. For the rest of the 24 countries that have no earnings data by occupation, we simply use the wage differential from a similar country that has a comparable level of GDP per capita and are geographically located close to one another. The wage data for the U.S. is extracted from the Occupational Employment Statistics database provided by the U.S. Bureau of Labour Statistics.

In row (4) of Table 4.6, we show that the main result is also robust to using lower rates of depreciation as the rates assumed by Corrado et al. (2009) might have been too high. Take R&D and organisation capital for example, other studies have suggested to use a rate of 15 percent to depreciate both capital stocks (Eisfeldt & Papanikolaou, 2013; Hall, 2007). For brand equity, we lower the depreciation rate to 50 percent following the empirical evidence surveyed in Bagwell (2007). In addition, the main result is not affected if the average growth rate of intangible investment, g, per equation (4.17) is calculated based on early years of observation (i.e. 1995-1999), since investment in intangibles were much lower in the 1990s than later on.

Last but not least, if other price proxies were used to deflate intangible investments, for instance the tangible investment price deflator, the GDP price deflator, or the non-farm business output price deflator, the resulting intangible capital stock correlate very highly (correlation above 0.98) and the main result of the analysis also remains largely unchanged (see the last three rows of Table 4.6).

Table 4.6: ROBUSTNESS ANALYSIS OF THE MAIN RESULT

	$\mathbf{var[log(y\prime)]}$	$\mathbf{var[log(y_{KRH})]}$	$\mathbf{VAF'}$	$\mathbf{\Delta}$
Baseline result from Table 4.5	0.445	0.177	39.8%	*+16%-points*
(1) Alternative OC	0.443	0.171	38.6%	*+15%-points*
(2) Dropping GRC&ESP	0.456	0.181	39.7%	*+16%-points*
(3) Dropping sample	0.403	0.160	39.7%	*+16%-points*
(4) Alternative δ_j	0.445	0.183	41.1%	*+18%-points*
(5) Alternative K_0 & R_0	0.445	0.177	39.8%	*+16%-points*
(6) Alternative price P^{BS}	0.445	0.173	38.9%	*+15%-points*
(7) Alternative price P^{GDP}	0.445	0.172	38.6%	*+15%-points*
(8) Alternative price P^{I}	0.456	0.173	38.9%	*+15%-points*

Notes: ‘Alternative OC’ denotes alternative measures of investment in organisation capital. ‘Dropping sample’ means Brazil, Egypt, Honduras, and Venezuela are dropped from analysis. Alternative prices in (6)–(8), denote intangible price deflator proxied by non-farm business output price deflator ($\mathrm{P^{BS}}$), the GDP price deflator ($\mathrm{P^{GDP}}$), and the tangible investment price deflator ($\mathrm{P^{I}}$).

Δ: denotes the difference in the explanatory power of the augmented model as compared to the basic model (i.e. VAF′-VAF) in percentage points.

4

4.5 Concluding remarks

Why do some countries produce so much more output per worker than others? We revisit this question by accounting for the role of intangible capital, a form of investment that has become increasingly more important in the fast-changing modern economy. Based on various data sources, we first develop a new intangible investment database that is consistent and internationally comparable for a sample of 60 countries and over a time span of 1995-2011. We find a high positive correlation between a country's level of GDP per capita and its investments in intangibles. In a development accounting framework, we show that the fraction of cross-country income variation accounted for by the observed differences in factor inputs increases substantially after taking intangible capital into account. In our baseline result, observed input differences can account for approximately 40 percent of income differences, which is notably higher than the 23 percent if only differences in physical and human capital are accounted for.

Furthermore, the potential of intangible capital to account for international income differences is likely to be greater than what the results in this chapter suggest, as the set of intangible assets we cover is only a subset of the full list of intangibles identified by Corrado et al. (2005).

Although the evidence we find are encouraging, it is important to note the limitations as well. First, there are still many unresolved yet highly important issues surrounding the measurement of intangible capital. For instance, we have not adequately addressed the issue of appropriate price deflators for the asset-specific intangible investments. Assumptions made in this regard may have non-trivially affected the quantitative results. Second, the standard 'one-size-fits-all' output elasticities of inputs (e.g. 1/3 or 1/4 for physical capital) are simplifications which may not reflect the reality. As noted by Inklaar and Timmer (2013), the explanatory power of variation in observed inputs could be larger if output elasticities of inputs are country- and year-specific. This limitation, however, does not discredit the contribution of this study to the literature as the results are comparable to earlier studies that have also assumed a common output elasticity of factor inputs (e.g. Caselli, 2005; Mutreje, 2014). Third, the analysis is based on capital stocks rather than capital services, which would have been a more appropriate measure for capital input since shorter-lived assets should have a larger return in production as it would be indicated by its user cost. But while these are limitations, our analysis is still a useful step forward. By focusing attention on low levels of investment in intangible assets in lower-income countries, we suggest a research agenda for trying to uncover the determinants of this low investment and thus a promising new direction for understanding international income differences.

Appendix

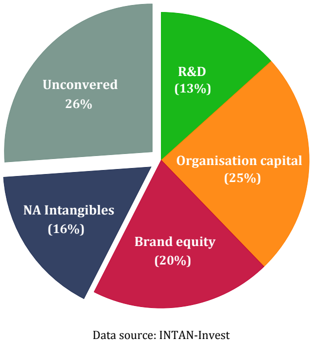
4.A Data construction

In this note, we describe in detail the data sources and estimation methods used to produce the global series of intangible investment for 60 economies and for the period 1995-2011 (see Table 4.A1 for the full list of economies covered). Given data constraint, the focus is placed on the construction of three major types of intangible assets that are not yet fully incorporated in the System of National Accounts (SNA): (1) scientific research and development (R&D), (2) own-account organisation capital, and (3) brand equity. According to the estimates of INTAN-Invest, a pioneering database that provides country-level intangible investment data for 27 EU countries plus Norway and the U.S., these three assets taken together account for nearly 60 percent of all the intangibles identified by Corrado et al. (2005, 2009).[24] Therefore, the estimates presented in this study should provide a fair representation of the cross-country investment patterns in intangible assets. Moreover, the set of economies we cover account for over 91 percent of the world gross domestic product (GDP),[25] which means that, if not all, the vast majority of the world's total investment in intangible capital is captured in this study.

To avoid the difficulty of measuring intangible investment in public sectors (i.e. Education, Health, and Public Administration), the research scope is restricted to merely cover the market sector of the economy.[26] Hence, about 80%-85% of aggregate economic activity is captured (see Appendix 4.B for more detailed discussions on the distinction between market and nonmarket sectors).

[24]The other six intangible assets are: computerised database, mineral exploration, artistic originals, new financial products, architectural and engineering designs, and firm-specific human capital.
[25]This is according to the GDP estimates in 2005 from the Penn World Table version 8.1.
[26]Since the pioneering work of Corrado et al. (2005, 2009), there is a general consensus on the measurement for private business spending on intangibles. While public intangibles are rife with both conceptual and operationalisation problems. A new research project named SPINTAN has been launched recently and it deals with public investment in intangibles specifically. This project, however, is still in its early phase and we are still far from reaching any consensus regarding the asset types to be measured as public intangibles as well as a sound metric for valuation.

Figure 4.A1: Asset Coverage and Country Coverage



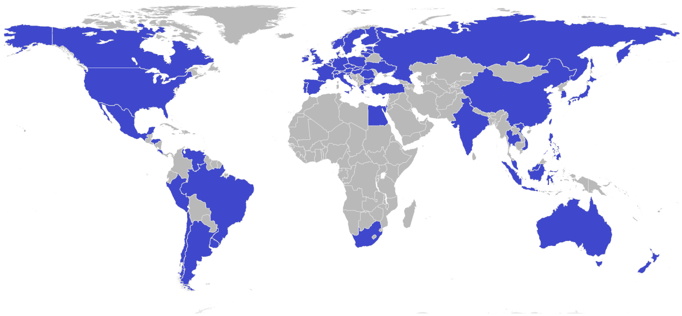


Table 4.A1: List of Economies Covered

Country	ISO	Country	ISO	Country	ISO	Country	ISO
Argentina	ARG	Estonia	EST	Latvia	LVA	Slovak Rep.	SVK
Australia	AUS	Finland	FIN	Lithuania	LTU	Slovenia	SVN
Austria	AUT	France	FRA	Malaysia	MYS	South Africa	ZAF
Belgium	BEL	Germany	DEU	Malta	MLT	Spain	ESP
Brazil*	BRA	Greece	GRC	Mexico	MEX	Sweden	SWE
Bulgaria	BGR	Honduras*	HND	Netherlands	NLD	Switzerland	CHE
Canada	CAN	Hong Kong	HKG	N. Zealand	NZL	Taiwan*	TWN
Chile	CHL	Hungary	HUN	Norway	NOR	Thailand	THA
China	CHN	India	IND	Peru	PER	Turkey	TUR
Costa Rica	CRI	Indonesia	IDN	Philippines	PHL	Ukraine	UKR
Croatia	HRV	Ireland	IRL	Poland	POL	U.K.	GBR
Cyprus	CYP	Israel	ISR	Portugal	PRT	U.S.A.	USA
Czech Rep.	CZE	Italy	ITA	Romania	ROU	Uruguay	URY
Denmark	DNK	Japan	JPN	Russia	RUS	Venezuela*	VEN
Egypt*	EGY	Korea	KOR	Singapore	SGP	Vietnam*	VNM

Notes: Economies marked with an asterisk indicate that for one of the three intangible assets estimated, one or more external data sources are used (e.g. business investment in R&D for Taiwan is derived from OECD). Estimates for other countries, on the other hand, are consistently based on the same data provider (e.g. data on business investment in R&D is solely taken from the UNESCO Institute for Statistics).

4.A1 Research and development

For the estimation of cross-country investment in (scientific) R&D, we primarily rely on the data provided by the UNESCO Institute for Statistics. To be specific, we obtain annual gross expenditures on R&D performed by Business Enterprises (BERD) for 56 countries and for the period 1996-2011.[27] For values that are missing from UNESCO, we first extrapolate them using the growth of the actual BERD values from the other data sources, such as OECD, Eurostat, and/or a country's own Statistical Office. Then, we linearly interpolate the data that are missing between two observed data points based on the logged variables (i.e. assuming a constant annual growth rate). The interpolation takes the following general form:

$$y^X = y_0^X + \left(y_1^X - y_0^X\right) \times \left(\frac{t - t_0}{t_1 - t_0}\right) \tag{4.A1}$$

where y_0 and y_1 denote two data points observed at year t_0 and t_1; y is the missing value needs to be interpolated at year t where $t_0 < t < t_1$, and X denotes the specific type of an asset, which in this case is R&D.

Countries with missing BERD

There are four countries (i.e. Brazil, Egypt, Honduras, and Venezuela) that warrant extra attention as none of them, to the best of our knowledge, provide any information on business investment in R&D.[28] As a result, we apply a rough proxy by using the share of BERD in GERD (i.e. $\frac{\text{BERD}}{\text{GERD}}$) from a 'similar' country to back out their business expenditures on R&D. Two countries are defined to be similar if they have identical or very similar intellectual property rights (IPR) protection scores and are geographically located close to one another. The assumption we make here is that the higher the level of IPR protection in a country, the larger the share of business investment in R&D. Despite being simplistic, this assumption is not without any plausibility. As shown in Figure 4.A2 where the strength of a country's IPR protection is significantly associated with the private share of R&D (Pearson's correlation coefficient is also highly significant at .01 percent).[29] The exact matching procedure for these four countries is shown in Table 4.A2.

[27]For Taiwan, the BERD data is alternatively extracted from the OECD database. As shown later in this appendix, there is a perfect match of the BERD data between UNESCO and OECD. Thus, even though BERD data for Taiwan is extracted from OECD, it is counted as taken from UNESCO.

[28]For Venezuela, there is even no data on GERD from the UNESCO Institute for Statistics. We alternatively extract the GERD data for Venezuela from the ECLAC database.

[29]The IPR index is only available quinquennially from 1960 to 2010. Thus, the years of observation used to plot Figure 4.A2 are discrete. We also considered dropping these four countries in the development accounting analysis and results remain largely unchanged.

Figure 4.A2: Relationship between IPR Protection and Business Share of R&D

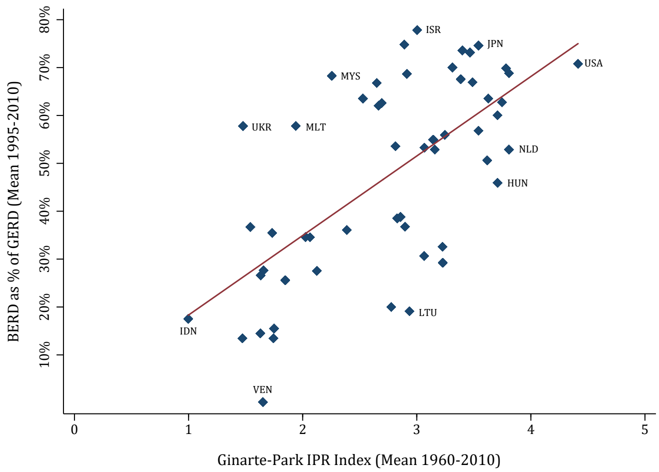


Table 4.A2: Matching the Share of BERD

Countries	Matched with	IPR Scores
Brazil	Mexico	5.5 - 5.2
Egypt	Kenya	4.6 - 4.6
Honduras	Argentina	4.5 - 5.5
Venezuela	Paraguay	3.2 - 4.1

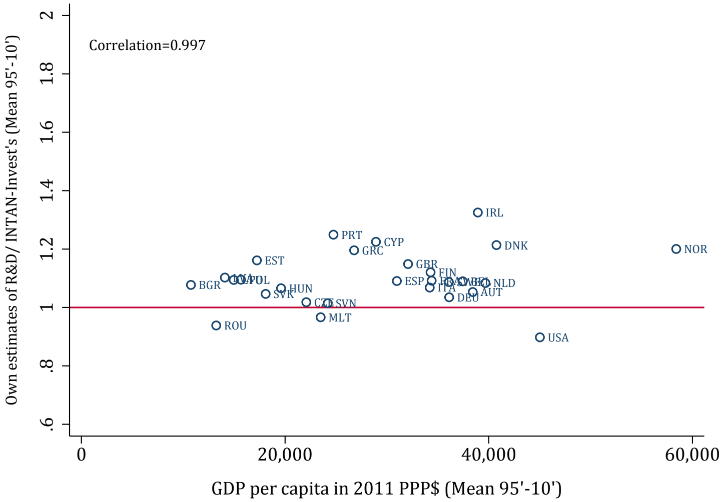
Notes: IPR scores are obtained from Intellectual Property Rights Index 2014.

Reliability check by comparing with OECD and INTAN-Invest

To examine how well the R&D numbers derived from the UNESCO Institute for Statistics line up with the other existing estimates, we compare them with two other prominent sources of data: (1) R&D investment by sector of performance provided by the OECD for a set of 34 countries and a time span of 1995-2011; and (2) estimates on business R&D investment reported by the INTAN-Invest database for 29 countries and over the period 1995-2010. With a (near) perfect correlation, comparisons with both data series assured the validity and reliability of our estimates of business investment in R&D. In fact, the investment figures of BERD are identical between UNESCO and OECD. As can be seen in Figure 4.A3, however, there is a somewhat wider range of dispersion when we compare our estimates with INTAN- Invest's. The estimates are generally larger than that of INTAN-Invest by about 10 percent. The largest discrepancy is observed in Cyprus for year 2004 where our estimates are close to twice as large. One of the reasons to explain the discrepancy is the difference in the methodology.

In INTAN-Invest project, R&D expenditures of the computer sector (K72) and the financial intermediation sector (J) are excluded from calculation in order to avoid double-counting with the other intangible investments in software and new financial products. Due to the lack of data, however, we are not able to exclude R&D investment of these two sectors and correct for the potential double-counting bias noted by the INTAN-Invest project.[30]

Figure 4.A3: Own Measure of Business Investment in R&D versus INTAN-Invest



4.A2 Organisation capital

Organisation capital or organisational structure is arguably the largest component of intangible assets and the hardest to measure. According to the estimates compiled by INTAN-Invest (see Figure 4.A1), this asset alone accounts for 25 percent of all intangibles. Rather than inventing or improving technologies like investment in scientific R&D, organisation capital is associated with innovation in methods, management practices, and business models. In the literature, organisation capital has two components: *own-account* and *purchased*. Due to the lack of data, we restrict the focus on the own-account component and further assume, a là Corrado et al. (2005, 2009), that own-account organisation capital can be represented by the value of managers' time

[30] As a robustness check, we tried to subtract the share of R&D investment of these two sectors from final estimation. According to the national accounts data provided by Eurostat, the sum of these two sectors is about seven percent (based on a cross-country average of 27 EU countries). As a crude measure, we downsized business investment in R&D by seven percent for all countries and years. This has little impact on the development accounting analysis.

spent on improving the effectiveness of business organisations and/or devising more efficient business models. Though it is a rather arbitrary number, we follow the broader literature by assuming that 20 percent of managers' time/wage is spent on enhancing organisational structures and this fraction holds true for all the 60 economies covered in this chapter. Therefore, in order to measure a country's investment in own-account organisation capital, we would need data on the total amount of managers employed in the economy and their corresponding annual wage. Investment in (own-account) organisation capital is then calculated as follows:

$$I_{c,t}^{OC} = \left(20\% \times W_{c,t}^{Managers}\right) \cdot EMP_{c,t}^{Managers} \tag{4.A2}$$

Data for managers

To retrieve data on employment by occupation, we rely on the International Labour Organisation (ILO) which, to the best of our knowledge, provides the most comprehensive information on labour statistics both in terms of time and country coverage. We obtain three datasets from ILO and as will be explained later, they are used complementarily during the employment data construction process. The first and the most important data, which we name it the benchmark data, is the number of employees by occupation using the International Standard Classification of Occupation (ISCO-88) from the ILOSTAT database. As described by ILO, this is a new database extending the previous data collection effort (i.e. LABORSTA) to more recent years (i.e. from 2008 onwards). From ILOSTAT we obtain employment data for all 60 economies covered in the sample and for the entire time period from 1995 to 2011.[31]

A detailed look into this data, however, shows that about 33 percent of the employment data on managers are missing. To fill the gaps that are observed between two data points, we again apply the linear interpolation technique per equation (4.A1). The other possibility to recover some of the missing data is to check whether the old labour statistics database (i.e. LABORSTA) may cover any information that is missing in the benchmark data (i.e. ILOSTAT). Consistent with the earlier ISCO-88 classification, we retrieve managers' employment data from LABORSTA for 59 countries and over the period of 1999-2008. After matching the two databases, we find that there are 77 observations having managers' employment statistics in the former but not in the latter database. Even though employment numbers from ILOSTAT and LABORSTA are very similar or even identical most of the time, there are cases where these two data series

[31] Other employment classifications are provided by ILO as well, but the 1988 version is used because it provides the most complete employment data by occupation.

differ by more than double.[32] To ensure consistency and comparability of the numbers by merging two databases, we extrapolate the benchmark data using the growth of LABORSTA numbers.[33] In other words:

$$EMP^{New}_{c,t-1} = EMP^{New}_{c,t} \times \left(\frac{EMP^{Old}_{c,t-1}}{EMP^{Old}_{c,t}} \right) \tag{4.A3}$$

where the superscripts *New* and *Old* refer to the benchmark (i.e. ILOSTAT) and LABORSTA databases. Since some of the employment data in early years (i.e. before 2000) are only available with an older version of the occupational classification (i.e. ISCO-68), we further extrapolate the missing values of early years using the growth of ISCO-68 numbers per equation (4.A3). A brief summary of the employment data construction process is shown in Table 4.A3. As can be seen in this table, extrapolation only takes place after linear interpolation is performed first.

Table 4.A3: Construction of the Employment Data

Order of integration	**Source**	**Methods**	**Missing(%)**
1.1	ILOSTAT ISCO-88 (BM)*	*Non*	32.84%
1.2	ILOSTAT ISCO-88 (BM)	*Interpolation*	29.90%
2.1	LABORSTA ISCO-88	*Interpolation*	
2.2	LABORSTA ISCO-88	*Extrapolate using its growth*	21.08%
3.1	ILOSTAT ISCO-68	*Interpolation*	
3.2	ILOSTAT ISCO-68	*Extrapolate using its growth*	16.27%

Notes: Linear interpolation, based on logged variables, is applied to all three databases to fill the gaps observed between two data points.

*BM: Benchmark data

One important issue to note about the employment data is that ILO only provides employment classification at the most aggregate level. Thus, it is not possible to separate managerial workers from legislators and senior officials under ISCO-88 classification or from administrative workers under ISCO-68 classification (see Table 4.A4 for a detailed outline of occupational classification). As a consequence, the estimates of own-account investment in organisation capital may well be larger than the conventional measure that focuses on workers with managerial titles only. This departure from the convention, however, is in line with the recent work of OECD (i.e. Squicciarini & Le Mouel, 2012)

[32]For Indonesia in year 2007, manager's employment level is reported in both LABORSTA and ILOSTAT but the former reports a total of 4,720,675 managers are employed in that year while ILOSTAT reports less than half of that (i.e. 2,160,000).
[33]For countries that have no data in ILOSTAT but do in LABORSTA, we simply copy the employment figures directly from LABORSTA. These countries include: Cuba, Honduras, Japan, Venezuela, and Zambia.

Table 4.A4: International Standard Classification of Occupations (ISCO-88 vs. -68)

ISCO-88	Profession group	ISCO-68	Profession group
0	Armed forces	0/1	Professional, technical and related workers
1	**Legislators, senior officials and managers**	**2**	**Administrative and managerial workers**
2	Professionals	3	Clerical and related workers
3	Technicians and associate professionals	4	Sales workers
4	Clerks	5	Service workers
5	Services workers and shop and market sales workers	6	Agriculture, animal husbandry and forestry workers, fishermen, hunters
6	Skilled agricultural and fishery workers	7/8/9	Production and related workers, transport equipment operators and labours
7	Craft and related trades workers	AF	Armed forces
8	Plant and machine operators and assemblers	X	Not elsewhere specified
9	Elementary occupations		
X	Not classifiable occupation		

Notes: The profession group denoted in **bold** letters are the occupations considered to contribute to the development of organisational structures. ISCO-68 is only used to complement the benchmark employment figures reported by ISCO-88.

Data source: ILOSTAT and LABORSTA databases from International Labour Organisation.

which calls for the inclusion of other non-managerial workers in measuring organisation capital. This is because those non-managerial titled workers may well be engaged in tasks that contribute to organisational development.

Wage data

It would be ideal to have the wage data on employment by occupation from the same data provider – ILO. This, however, was not possible due to the extremely scant data ILO provides on income by occupation. The income data is reported for a limited sample of 35 countries and for no more than three years of observation (i.e. 2009, 2010 and 2011). As a result, the wage data has to be externally imputed and we do so in two steps using two data sources: the Penn World Table version 8.1 (PWT) database and the Occupational Employment Statistics (OES) provided by the U.S. Bureau of Labour Statistics. First, we extract the data on annual income for management occupations from OES and denote it by $W_{BLS}^{Managers}$.[34] Then, we calculate the wage rate of an average worker for all 60 economies using data from PWT 8.1 as follows:

$$W_{c,t}^{Mean} = \left(\frac{labshare \times cgdpo \times pl\_gdpo}{emp} \right)_{c,t} \times xr_{c,t} \tag{4.A4}$$

where *labshare* indicates the share of labour compensation in GDP at current national prices; *cgdpo* is the output-side GDP calculated at current PPPs (denominated in 2005 USD); *pl_gdpo* denotes the price level of GDP; *emp* is the total number of persons engaged in production; and *xr* is the market exchange rate needed to convert currency units back to national currencies. Combing these two wages, we can derive a year-variant wage differential (or relative wage) between the managers and an average worker for the U.S. as follows:

$$R_t^{US} = \left(W_{BLS}^{Managers} / W_{PWT}^{Mean} \right)_t^{US} \tag{4.A5}$$

The evolvement of this relative wage R is plotted in Figure 4.A4. Because of the change of the use of Standard Occupational Classification from five-digit to six-digit in 1999, it was only possible to retrieve consistent U.S. wage data for years between 1999 and 2011.[35] To complete the estimation for the whole period, the relative wage is held constant to the last value available. Assuming that the wage differential between managers and average workers is the same in other countries as in the U.S. (i.e. R

[34] This is the annual wage of managers averaged across all different types. It is coded as 11-0000 according to the Standard Occupational Classification 2010

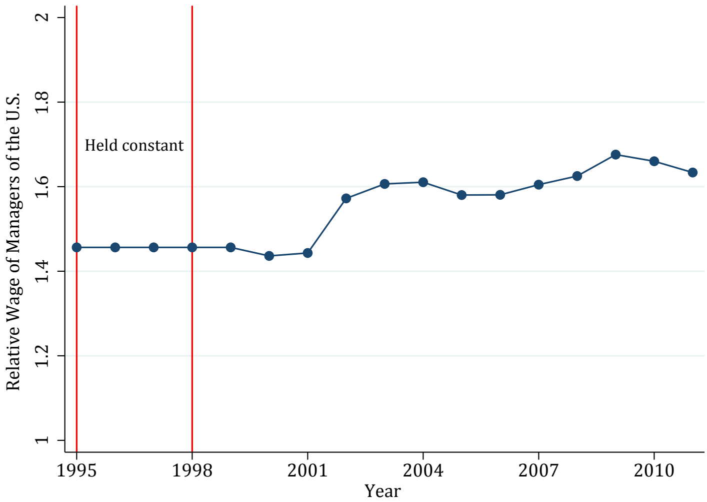
[35] No clear guideline on the matching between the five-digit SOC and the six-digit SOC are provided.

constant across countries), it is then possible to back out the wage rate of managers for all the other economies as follows:

$$W_{c,t}^{Managers} = R_t^{US} \times W_{c,t}^{Mean} \tag{4.A6}$$

which in turn enables us to estimate the annual investment flows in own-account organisation capital per equation (4.A2).

Figure 4.A4: Relative Managers' Wage of the U.S.

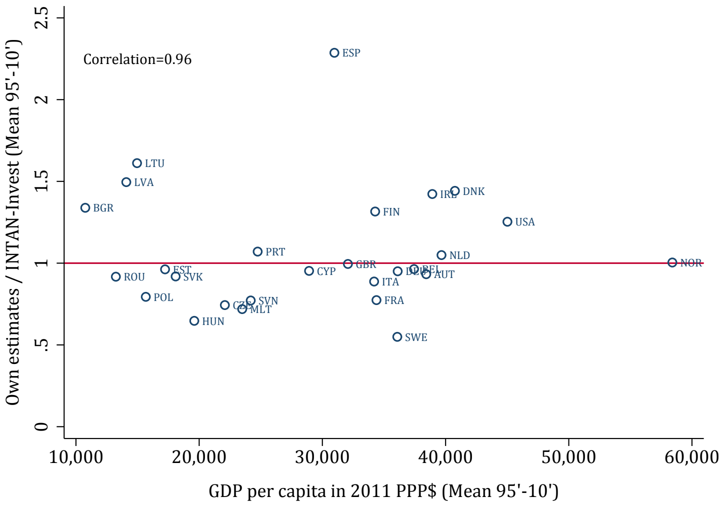


Reliability check by comparing with INTAN-Invest

To check how well our estimates, using equation (4.A2), align with the existing measure, we compare the estimates with INTAN-Invest (see Figure 4.A5). It is worth noting that it is not our goal to have a perfect match between these two investment series as there are both methodological and data differences. Investment in organisation capital provided by INTAN-Invest has two components: in-house produced and externally purchased. As previously noted, we merely focus on the estimation of the former and omit the latter. Since most of organisation capital are in-house produced (Squicciarini & Le Mouel, 2012), the estimates constructed should be in the same ballpark as INTAN-Invest's, despite of the differences in coverage.

With a correlation of 0.96, the plausibility of the our measure of investment in organisation capital is warranted. In addition to this high correlation, the estimates

Figure 4.A5: Own Measure of Investment in OC versus INTAN-Invest



also fairly closely resemble those of INTAN-Invest. The mean and the median of the ratio of our estimates to INATN-Invest's are at 0.99 and 1.29. If Greece and Spain are excluded, two countries that we elaborate on later, the similarity between the two investment series improves significantly. The mean and the median of the ratios become 0.962 and 0.998. This suggests that the difference between our estimates and INTAN-Invest's for a sample of 27 countries (i.e. after excluding GRC and ESP) is, on average, less than 0.1 percent.

Greece and Spain are two notable outliers whose investment in own-account organisation capital are significantly larger than the estimates suggested by INTAN-Invest. A careful look into the data shows that the cause of this large discrepancy is primarily due to the difference in the coverage of the number of managers, which is a potential source of discrepancy we anticipated ex ante. The fact that Greece and Spain are affected most is because the difference between strictly defined and broadly defined managers is anomalously large for these two countries. As shown in Figure 4.A6, the sum of managers, legislators and senior government officials is generally less than twice the amount of corporate managers. For Greece and Spain, however, this difference is more than 8 and 4 times, respectively. This seems to suggest that unlike other EU countries, there is a disproportionately large amount of governmental managers employed in Greece and Spain than corporate managers. The failure to exclude them caused significant (upward) bias for the estimates of these two countries. As discussed in the main text, findings are not affected if these two countries were left out from the development accounting analysis.

Figure 4.A6: Legislators, Senior Officials, Managers versus Managers

4.A3 Brand equity

As the most valuable assets many companies possess (e.g. think of Facebook or Uber, their names probably worth much than their documented property and machinery), brand equity is another major type of intangible we measure in this study. The idea of brand equity was born in the U.S. in the 1980s when companies began to realise that patiently building up brands is more enduring to boost sales than other means, as it allows them to hold on to customers, win new ones and provide launching pads for new products. Most brands are closely associated with advertising and marketing activities, which are the most common ways of building up a brand. Thus, we follow the convention by decomposing brand equity into these two components. Closely in line with the recent work of Corrado and Hao (2014), we reproduce the global perspective on brand investments using two international database: World Advertising Research Centre (WARC) and European Society for Opinion and Marketing Research (ESOMAR). The former is a privately owned company that publishes the official advertising expenditure figures for 84 countries and for years dating back to the 1980s; the latter issues market research spending data for about 80 countries and for some of them the data is available since 1988.

As noted by Corrado and Hao (2014), these two data sources are likely to underestimate the actual amount of expenditures. For advertising, WARC does not include direct mailing and production costs. This, according to their calculation based on the Coen media-structured advertising database, is a significant omission. If one adds direct mail advertising to WARC's estimates for the U.S., the overall advertising spending figure of the U.S. would increase by 32 percent. In the case of the U.K., the magnitude of such a downward bias is about 7 percent, according to WARC's own calculation.

As for the market research spending figures provided by ESOMAR, it is likely to be overly conservative as well, since it only focuses on traditional market research activities while newer activities associated with the internet are not yet included in their (official) estimation. An external independent research, commissioned by ESOMAR, extends the conventional market research activities to include seven more newer ones and found that the expanded set of marketing activities led to spending figures that were 60 to 70 percent larger in the U.S. and the U.K., and 20 percent larger in Argentina.[36] This finding points to the fact that the marketing industry is undergoing structural changes and the current focus on traditional marketing activities is simply insufficient to capture the actual level of spending in market research activities. Despite of the known risk of having a downward bias, we still choose to rely on these two data sources for its comprehensive data availability.

Estimation method for investment in brand equity

It is well-documented in the existing literature on advertising longevity that only major campaign type of advertising spending is likely to generate long-lasting benefits to the development of a brand. Therefore, not all advertising spending can be counted as investment. We follow Corrado et al. (2005, 2009) and Corrado and Hao (2014) by applying a capitalisation factor (d) of 60 percent.[37] This capitalisation factor is also found to be in line with the U.K. intangible asset survey (Awano, Franklin, Haskel & Kastrinaki, 2010).

In two country-specific studies on the U.K. and Sweden, Marrano, Haskel and Wallis (2009) and Edquist (2011) used figures from the supply-use tables on business purchases of advertising and market research to measure investment in brand equity. These studies

[36]According to the Market Research Handbook (2007), the traditional market research activities include: (1) market measurement, (2) media audience research, (3) stakeholder measurement, (4) market modelling, (5) new product/service development, (6) usage and attitude studies, (7) advertising/brand tracking, (8) advertising pre-testing, (9) opinion research/polling, (10) qualitative/focus groups, (11) business-to-business studies, (12) other omnibus/shared costs survey, and (13) others. The additional activities added by the external research commissioned by ESOMAR include: (1) marketing reports and research, (3) media monitoring, (3) sample and panel provides, (4) web traffic measurement, (5) social media communities, (6) survey software, and (7) information technology and telecom measurement research.

[37]Effects that last more than one year, a distinction used widely by national accountants in separating current production costs from expenditures that expand future productive capacity.

find that advertising media expenditures understates the actual total consumption of advertising services and they reckon that the underestimation is about 39 percent. In light of their suggestion and to remain consistent with Corrado and Hao (2014), we also scale up the advertising media spending figure by multiplying the so-called MHW-Edquist adjustment factor (i.e. $\gamma_{adv} = 1.39$) to measure long-lived investment in advertising. In addition, market research spending provided by ESOMAR only captures the *purchased* component, while the *in-house* production of market research is omitted. In the case of the U.S., the own-account component based on compensation of marketing managers is about equal in size to the purchased market research activities (Corrado & Hao, 2014). This aligns with the prior assumption used in Corrado et al. (2009) of doubling market research spending to account for own-account component. In sum, investment in brand equity is estimated as follows:

$$I_{c,t}^{BE} = \underbrace{\left(d \cdot \gamma_{adv} \cdot E_{c,t}^{adv}\right)}_{\textit{Investment in advertising}} + \underbrace{\left(\gamma_{mkt} \cdot E_{c,t}^{mkt}\right)}_{\textit{Investment in market research}} \tag{4.A7}$$

where γ denotes the adjustment factor (i.e. 1.39 for advertising and 2 for market research), E is the expenditure data obtained from WARC and ESOMAR, and d is the capitalisation factor of 60 percent to capture long-lived advertising. To note, we implicitly assume that in-house marketing spending equals out-house spending in all countries.

Comparison with the existing estimates

Since both estimation method and data sources are identical to what is used in Corrado and Hao (2014), our estimates in principal should coincide with theirs. Due to the fact that their global series on brand investment estimates are not yet publicly available, a direct one-to-one estimate comparison cannot be made. As an alternative, we performed a somewhat crude comparison by replicating their plot on the relationship between brand investment and level of economic development across a set of 17 countries and they resemble quite well.[38] As an additional check, we further compare our investment in brand equity with the estimates from INTAN-Invest. On average, the estimates are somewhat (i.e. 20%) smaller than the numbers suggested by INTAN-Invest, but it is reassuring that these two series have a very high correlation of 0.92.

[38]For conciseness, these plots are intentionally omitted but are available upon request.

4.A4 Dealing with missing values

Like any other data construction works, one of the major difficulties encountered in this project is that not all countries have the data available for all the years that we aim to cover. The data missing patterns also differ significantly across countries and asset types. For intangible asset R&D, some countries only have one year of observation available (e.g. Vietnam), while a smaller set of data-rich countries (e.g. the U.K. and the U.S.) only has one year of observation missing. In order to complete the investment series for each intangible asset, we apply: (1) linear interpolation technique based on the logged variables, per equation (4.A1), to fill in the values that are missing between two data points; and (2) backward and forward extrapolations using the average growth of each investment/GDP series observed in the first (last) five years:

$$I^X_{c,t-1} = \left(\frac{S^x_{c,t}}{1+r}\right) \times NGDP_{c,t-1} \qquad I^X_{c,t+1} = S^x_{c,t} \cdot (1+r) \times NGDP_{c,t-1} \tag{4.A8}$$

where the superscript X denotes the intangible asset under concern (i.e. R&D, organisation capital, and brand equity); S denotes the first/last observable share of intangible asset X in GDP, and r represents the average growth rate of this share observed for the first/last five years (i.e. $\sum_{t=1}^{5} S/5$). Table 4.A5 provides an overview of the data missing patterns. As can be seen, about 22%–32% of the investment series are not estimated based on the real data, but are imputed. It could be argued that given high rates of depreciation assumed for organisation capital (40%) and brand equity (60%), it is not needed to have series for them going back to 1995 if the development accounting analysis is based on 2011. Focusing on more recent years (e.g. 2003–2011 for organisation capital), however, does not help much to reduce the amount of imputations.[39] As a result, we choose to have equally long series for those three intangible assets.

4

Table 4.A5: Share of Missing Observations by Asset-type

Missing (%)	**R&D**	**O.C.**	**Brand Equity**
Originally	21.96%	32.84%	24.71%
After interpolation	16.08%	29.90%	20.88%
After extrapolation	0%	0%	0%
N (60 × 17)	1020	1020	1020

[39]For investment in organisation capital, the reduction in imputation is merely two percent less (30.75%).

4.B Market versus nonmarket sectors

In this section we discuss the distinction between the market sector and the nonmarket sector for *output*, *employment*, and *investment*. Similar to the definition used in the EU KLEMS project, we regard NACE industries Revision 1: Public Administration and Defense (L), Education (M), and Health and Social Work (N) as nonmarket sectors and the remaining ones (A through K, plus O) make up the share of the market economy.[40]

4.B1 Market output versus nonmarket output

The nonmarket output share for country c at year t is calculated as follows:

$$Share^{NM}_{c,t} = \frac{\left(L^{VA}_{c,t} + M^{VA}_{c,t} + N^{VA}_{c,t}\right)}{GVA_{c,t}} \tag{4.B1}$$

where L, M, and N denote value added of the nonmarket industries; and GVA denotes total value added of the entire economy. Since there is no one single database providing a consistent sectoral breakdown of output for all 60 economies, we complementarily calculate the nonmarket share using various data sources (see Table 4.B1).

There are, however, two economies (i.e. Hong Kong and Singapore) require some further explanation as neither of them provide detailed data on public output. As an alternative, we back out their output of the nonmarket sectors using two other data sources: the 10 sector database compiled by the Groningen Growth and Development Centre (GGDC) and the United Nations National Accounts (UN NA) data. The former provides output data for industry J and K (Finance, insurance, real estate and business activities) and industry O and P (Community, social and personal services); while the latter provides output data at a more aggregate level for industries J through P (denoted as 'Other activities' in the UN NA data). Given these, output share produced by industry L, M, and N can be recovered as:

$$Share^{NM}_{c,t} = \frac{\left(J\_P^{UNNA}_{c,t} - J\_K^{GGDC}_{c,t} - O\_P^{GGDC}_{c,t}\right)}{GVA^{GGDC}_{c,t}}; \qquad c \in (HKG, SGP) \tag{4.B2}$$

Out of 1020 observations (60 countries 17 years), there are four countries with a total number of only 17 missing values. To complete the series of the share of nonmarket

[40]In EU KLEMS, real estate activities (K70) is also part of the non-market economy due to measurement difficulties (see O'Mahony & Timmer, 2009). We, however, did not follow EU KLEMS to exclude K70 from the market economy because for nearly one-third of the countries we cover, their GDP data are not detailed enough to isolate real estate activities. To keep the definition of market economy consistent across countries, real estate activities (K70) are therefore part of the market economy.

Table 4.B1: Data Sources and Variables Used for Output

Data Sources	Countries	Variables used
WIOD (SEA)	39	VA of industry L, M, N, and total industries
GGDC (10-Sector database)	7	VA of Government services, and total industries
ECLAC	5	VA of Pub.Admin, Edu., Health, and total industries
OECD Stat.	4	VA of B1GVO_Q and B1GVA (ISIC Rev.4)
National Statistics office	3	VA of industry L, M, N, and total industries
UN National Accounts	2	VA of Other activities (ISIC J_P)

Notes: United Nations National Accounts data is used in conjunction with GGDC's 10-sector database for calculating the nonmarket output share of Hong Kong and Singapore.

output, we resort to using the UN NA data and extrapolate (backward and forward) as follows:

$$\underbrace{LMN_{t\pm1} = LMN_t \times \left(\frac{J\_P^{UNNA}_{t\pm1}}{J\_P^{UNNA}_{t}}\right);}_{extrapolate\ nonmarket\ output} \qquad \underbrace{GVA_{t\pm1} = GVA_t \times \left(\frac{GVA^{UNNA}_{t\pm1}}{GVA^{UNNA}_{t}}\right)}_{extrapolate\ total\ value\ added} \tag{4.B3}$$

The share of the nonmarket output could be as low as 4 percent in Singapore to as high as nearly 25 percent in Denmark.

4.B2 Market employment versus nonmarket employment

4

The primary source of data we use for employment is the labour statistics provided by the International Labour Organisation (ILO). In particular, we obtain employment measured by the number of employees (i.e. paid-employment and self-employment) detailed at 1-digit sectoral level using ISIC Rev.3 classification for an unbalanced panel of 57 countries. The employment share of the nonmarket sector is calculated as:

$$EMP\_Share^{NM}_{c,t} = \frac{\left(L^{EMP}_{c,t} + M^{EMP}_{c,t} + N^{EMP}_{c,t}\right)}{TOT\_EMP_{c,t}} \tag{4.B4}$$

where L^{EMP}, M^{EMP}, and N^{EMP} denote the number of employees working in nonmarket sectors; and TOT_EMP denotes the total employment of the economy.

Out of the 969 observations that we retrieve from ILO (57 countries 17 years), over 28 percent of the values are missing. We first apply linear interpolation per equation (4.A1) to fill the gaps that are observed between two data points (13 values are interpolated) and then extrapolate the remaining missing values complementarily using various external data sources (see Table 4.B2). The extrapolation takes the following general form:

$$EMP\_Share_{t\pm1}^{ISIC\ Rev.3} = EMP\_Share_{t}^{ISIC\ Rev.3} \times \left(\frac{EMP\_Share_{t\pm1}^{Data}}{EMP\_Share_{t}^{Data}}\right) \tag{4.B5}$$

where *Data* indicates data origins (e.g. ISIC Rev.2, WIOD, GGDC). After extrapolation, the amount of missing data went down from 28% to about 8% and we hold the share constant to the last value available to complete the series of nonmarket employment share for this set of 57 countries.

Table 4.B2: Data Sources and Variables Used for Employment

Data origins	Used for	Variables used
ILO (ISIC Rev.3)	BM data	Employment at 1-digit sector level (ISIC Rev.3)
ILO (ISIC Rev.2)	Extrapolation & BM	Employment at 1-digit sector level (ISIC Rev.2)
WIOD (SEA)	Extrapolation	Number of employees by industry (EMPE)
GGDC (10-Sector database)	Extrapolation	Total persons engaged by industry (EMP)

Notes: There are three economies with their nonmarket employment numbers approximated using the employment data of ILO ISIC Rev.2 (i.e. Hong Kong, Honduras, and Venezuela).

As for the other three economies (i.e. Hong Kong, Honduras, and Venezuela) that do not provide any employment information on industry L, M, or N, we try to proxy it using more aggregated sectoral employment data classified by ISIC Rev.2. From ILO, there is employment information available for sector *Community, Social and Personal Services*, which corresponds to the sum of industries of L through Q in ISIC Rev.3. Based on a set of 23 countries, it is found that the employment level of industries L through Q is on average about 1.5 times more than the employment of industry L, M, plus N. Using this ratio as a rough indication, the employment share of nonmarket sectors for Hong Kong, Honduras, and Venezuela is measured as follows:

$$EMP\_Share_{c,t}^{NM} = \frac{\left(L\_Q_{c,t}^{Rev.2}/1.5\right)}{TOT\_EMP_{c,t}^{Rev.2}} \tag{4.B6}$$

The employment share of nonmarket sectors could be as low as 5 percent in Vietnam to as high as over 30 percent in Scandinavian countries.

4.B3 Market investment versus nonmarket investment

As for the distinction between investment in market sectors and nonmarket ones, we rely on Social Economic Accounts data of the World Input and Output database (Timmer, Erumban, Los, Stehrer & de Vries, 2014) which provides detailed sectoral breakdown of gross fixed capital formation (GFCF). For a set of 39 economies covered in the sample, the investment share of nonmarket sectors is calculated as follows:

$$GFCF\_Share^{NM}_{c,t} = \frac{L^{GFCF}_{c,t} + M^{GFCF}_{c,t} + N^{GFCF}_{c,t}}{TOT\_GFCF_{c,t}} \tag{4.B7}$$

where L^{GFCF}, M^{GFCF}, and N^{GFCF} denote GFCF of nonmarket sectors; and TOT_GFCF denotes the total investment flows of the economy. The investment share of the nonmarket sector for those 39 economies ranges from slightly over 5 percent in Russia to about 23 percent in Taiwan. As there are no other data available to breakdown GFCF by sectors, we use an average share of those 39 economies for the remaining ones that are not covered by WIOD (i.e. 12 percent).[41]

[41]The sectoral GFCF data provided by WIOD often do not cover the last 2 or 3 years (i.e. 2010 and 2011). We keep the last observable share constant to the complete the data series.

CHAPTER 5

Do stronger intellectual property rights lead to more R&D intensive imports

5.1 Introduction

Unlike the preceding chapters where the focus is centred around the impact of intangible capital per se. In this chapter we take a different perspective by examining how the stringency of intellectual property rights (IPR) protection could serve as a tool for countries with a slow pace of investment in intangibles to attract knowledge-intensive goods via international trade.

IPR protection is generally assumed to stimulate innovation and growth (Duguet & Lelarge, 2012; Gould & Gruben, 1996; Sakakibara & Branstetter, 2001). This can be through providing incentives for innovative activities by domestic firms, but might also due to a higher level of technology diffusion from abroad. One important diffusion channel is the import of sophisticated products. According to the theory formalised by Maskus and Penubarti (1995), increased IPR protection in the domestic market can affect imports in two opposing ways. On the one hand, foreign firms have a greater incentive to export their products to the domestic markets, as IPR protection reduces the risk of piracy by domestic competitors. This is termed the *market expansion effect* as foreign firms increase sales in the market. On the other hand, by reducing the ability of local domestic firms to imitate foreign products, the exporter has greater market power which could lead the foreign firm to curtail sales. This countervailing effect is coined the *market power effect*. It is theoretically ambiguous which effect dominates since both effects are at work and may cancel each other out. A large empirical literature generally finds that higher levels of IPR protection stimulate trade flows for manufacturing products, suggesting the market expansion effect tends to be stronger (Awokuse & Yin, 2010; Falvey, Foster & Greenaway, 2009; Rafiquzzaman, 2002; Weng, Yang & Huang, 2009).[1]

While the market expansion effect of increased IPR protection on trade is well-established, there is little agreement and evidence on the possible heterogeneity in responsiveness of imports to IPR protection. This evidence is important because not all IPR protection is related to products that might provide technology spillovers. For example, it might be related to protection of brand names of consumer products mainly leading to imports that embody little technological know-how, in contrast to, say, machinery. From the perspective of enhancing growth, one would be interested in the impact of IPR on imports of technologically-advanced products. This is especially relevant for low- and middle-income countries, as importing technology intensive products can be an important channel of knowledge diffusion from advanced countries and thus be a path towards higher growth and income levels (Keller, 2004).

Several studies that have attempted to shed light on this issue have produced mixed results. On the one hand, strengthening IPR protection is found to have no significant impact on products with greater technology embodiment (Co, 2004; Fink & Primo Braga, 1999; Maskus & Penubarti, 1995). Whereas, others find increased IPR protection has a particularly strong impact on products that are knowledge-intensive (Awokuse & Yin, 2010) or industries that are patent-sensitive (Ivus, 2010). Besides their obvious differences in the data sample used, a more fundamental reason that could explain the mixed results is the empirical approach employed. All these studies relied on dividing import flows by product and separately analysing the subsample in probing how stronger IPR protection affects trade. Though helpful and intuitive, the approach is not suited to examine a differential effect as it does not directly compare and test whether the difference is statistically significant across products in terms of technology content.

The main contribution of this chapter is to provide systematic evidence on the differential effects that variations of IPR have on trade, contingent upon the technology intensity of a product category. This evidence can be seen as an important addition to the continuing debate regarding the impact of the contentious agreement on the Trade-Related Aspects of Intellectual Property Rights (TRIPs) signed in 1994.[2]. TRIPs is an

[1]The only study that has found clear evidence supporting the presence of the market power effect is by Smith (1999).

[2]The major controversy over the TRIPs agreement is centred around the balance between the incentives to encourage new inventions and the ease with which developing countries can access the patented products and technology. A salient example is the pharmaceutical industry. The development costs for new drugs can be very high and it may not be developed without a large (monopolistic) return ensured by patent protection that is respected across the globe. The worldwide adoption of a uniformly strong patent protection would, however, raises the probability of very expensive treatments for the growing epidemics that makes the least-developed countries worse off (Kyle & McGahan, 2012)

international agreement administered by the World Trade Organisation that sets the minimum standards for various forms of intellectual property regulation. This agreement came into effect on 1 January 1995. Has tougher IPR protection mandated by TRIPs really restricted trade in high-tech products and strengthened the monopolistic power of a few innovators, as believed by the opponents of the agreement? To answer the question, we follow the empirical strategy pioneered by Rajan and Zingales (1998) and proxy for the technology intensity of an imported product by the extent to which the originating industry invests in R&D. We then interact the resulting intensity indicator of the product categories with the strength of IPR protection of the importing country. This method is econometrically more appealing than what has been used in the existing literature, as (1) the interaction term provides a direct test for the statistical significance of the differences between product categories with varying degrees of R&D intensity; (2) it provides more convincing evidence on causality since this approach is less subject to criticism about an omitted variables bias or model misspecification (Rajan & Zingales, 1998); and (3) we could also, for the first time, quantify the magnitude of the effect-differentials across product categories. For instance, rather than merely stating that increased IPR protection has a larger impact on R&D-intensive products, we now show by how much more the trade value will increase for a product category that is more R&D intensive relative to one that is less R&D intensive. This quantification is interesting in its own right but it can also be of great value to policy makers in assessing the economic significance of upgrading the IPR system in the country.

The empirical analysis is based on data for manufacturing imports classified by 18 different product categories for a sample of 119 countries and over the period 1976-2010. The stringency of IPR protection of the country is measured by an index developed by Ginarte and Park (1997). Given the nature of IPR index, all the data are grouped into 5 year periods in this study. In other words, the data used in the analysis cover the following years: 1976, 1980, 1985, 1990, 1995, 2000, 2005, and 2010. The main findings are that the impact of IPR on imports is indeed significantly positively correlated with R&D intensity. We find that more stringent IPR protection leads to a 22 percent faster increase in the value of imports for products at the 90th percentile of R&D intensity (Office, accounting and computing machinery) than for products at the 10th percentile (Textiles, leather, and footwear). This finding remains robust to alternative measures of R&D intensity of product categories and to using a modified IPR index that corrects for the actual enforcement of patent laws in the country.

By splitting the analysis into pre- and post-TRIPs time periods (i.e. 1976-1990 versus 1995-2010), we show that the differential effect of IPR is significantly larger in the latter period. This finding supports the notion that the TRIPs agreement stimulates, rather than restricts, trade flows and it seems that the agreement is especially conducive to trading technologically advanced products. If countries are further divided into three different groups according to their income levels, we find that imports by middle-income countries are most sensitive to changes in IPR protection. Splitting the source of imports by different income groups, we also show that the differential effect of IPR is only present for imports coming from the middle-income countries. This result seems to suggest that rather than attracting more technology-intensive products from advanced economies as one would expect after strengthening IPR protection, the middle-income countries only attracted more imports from countries of its own income group.

The remainder of this chapter proceeds as follows. Section 5.2 describes the main empirical strategy and the data used for analysis. Results and sensitivity analyses are presented in Section 5.3. Section 5.4 provides concluding remarks.

5.2 Empirical strategy and data

In this section, we discuss the econometric approach to analysing the differential effects of strengthening IPR protection on manufacturing imports, followed by a description of the data and methods used to construct the key variables of interest.

5.2.1 Econometric specification

The majority of the existing studies focused on examining the main effect of IPR on trade and relied on dividing imports by product category to identify the differential effect. This approach, however, is not suitable to examining the heterogeneity in responsiveness of trade to IPR protection as it has two major limitations. First, the number of observations diminishes greatly after splitting the sample by product. This makes it harder to find a significant effect. Second, even if the effect can be identified as in, for example, Awokuse and Yin (2010), it cannot be directly compared or tested whether the difference is statistically significant across products, let alone drawing implications about the economic significance of the differential effect. To analyse the differential effect of IPR, we adapt from the approach of Rajan and Zingales (1998) by estimating the following equation:

$$lnM_{c,i,t} = \beta \cdot [IPR_{c,t} \times RD_i] + \eta_{c,t} + \eta_{i,t} + \epsilon_{c,i,t} \tag{5.1}$$

where the value of imports M for country c, product group i, in year t is expressed in natural logarithm; IPR denotes the stringency of a country's IPR protection over time; RD is the product-level indicator for technology intensity, as measured by R&D expenditures as a percentage of value added of the industry which delivered the import; $\eta_{c,t}$ represents all the country-level factors that can vary with time, such as income levels, openness to trade, price indexes, and institutional quality; $\eta_{i,t}$ captures all the product-level factors that can vary over time, such as global trends in productivity and prices or in the demand for a product. Note that these two set of dummies also capture country–, product–, and time–specific fixed effects so that including them separately is not needed. $\epsilon_{c,i,t}$ is the idiosyncratic error term.

The coefficient β measures whether more stringent IPR protection leads to higher values of imports of products that are more R&D-intensive and if so, the size of the coefficient would reflect the magnitude of this differential effect. Given the theory that technologically advanced products are more prone to imitation and hence more sensitive to changes in IPR protection, β is expected to be positive and significant when the market expansion effect dominates.

5.2.2 Proxy for IPR Protection

As widely used in the literature, the strength of a country's IPR protection is measured by an index developed by Ginarte and Park (1997) and further extended by Park (2008). This index, which we will indicate by G-P in the remainder, is constructed for 122 countries and quinquennially for the period 1960-2010. Five facets of patent laws are captured in the G-P index: the extent of IPR coverage, membership in international patent agreements, provisions for loss of protection, formal enforcement mechanisms, and duration of protection. Each component was further decomposed into characteristics determining its effective strength. For instance, the extent of coverage refers to the patentability of various kinds of inventions in a country, ranging from the patentability of chemical products to the existence of utility models. Membership in patent agreements indicates the number of international treaties a country is a signatory. Each of these subcomponents was assigned a value of one if present and zero if absent, with the component score being the sum of these values as a percentage of the maximum value. Adding up the component scores, the final G-P index is indicated by a continuous value ranging from zero to five, with a higher number signalling more stringent patent protection. This index is considered as the best indicator available in the literature and it has the major advantage over the other popular measure, the index of Rapp and Rozek (1990), in that it is constructed for different years which allows for analysis of the index over time. The Rapp-Rozek index, on the other hand, is merely available for one single year. Conceptually, the G-P index is also preferred because by considering various facets of patent protection in greater detail the G-P index is more nuanced to reflect variations in patent laws than the subjective and unit-incremental approach used in the Rapp-Rozek index (Kanwar & Evenson, 2009).[3]

In general, the world has witnessed a strong increase in IPR protection during the past half-century. The world average of the G-P index value soared from 1.26 in 1960 to 3.33 in 2010. The country that has upgraded most in terms of the strength of IPR protection is (South) Korea, with no IPR protection in 1960 to become one of the most highly IPR protected nations in 2010 (IPR index value 4.33). Somalia, on the other hand, experienced the smallest increase in IPR protection, with an index value of 1.33 in 1960 and 1.46 in 2010. It may not come as a surprise that the U.S., according to the G-P index, provides the best IPR protection across all countries at any point in time (3.83 in 1960 to 4.88 in 2010). Myanmar offers the poorest IPR protection in the world (index value of 0.2 in 2010). If countries are divided into three different groups depending on their income levels, it can be seen that the middle-income countries have strengthened their patent protections most during the period of investigation and the largest increase in IPR protection, across all income groups, took place in 1995, the year in which the TRIPs agreement came into effect.

Table 5.1: The Means of the Ginarte-Park IPR Index

	1975	**1980**	**1985**	**1990**	**1995**	**2000**	**2005**	**2010**	**1975-2010**
High-income	2.48	2.90	3.07	3.28	4.02	4.29	4.33	4.33	74.6%
Mid-income	1.41	1.49	1.52	1.59	2.31	2.92	3.23	3.33	135.2%
Low-income	1.28	1.37	1.50	1.54	1.85	2.20	2.56	2.65	107.5%

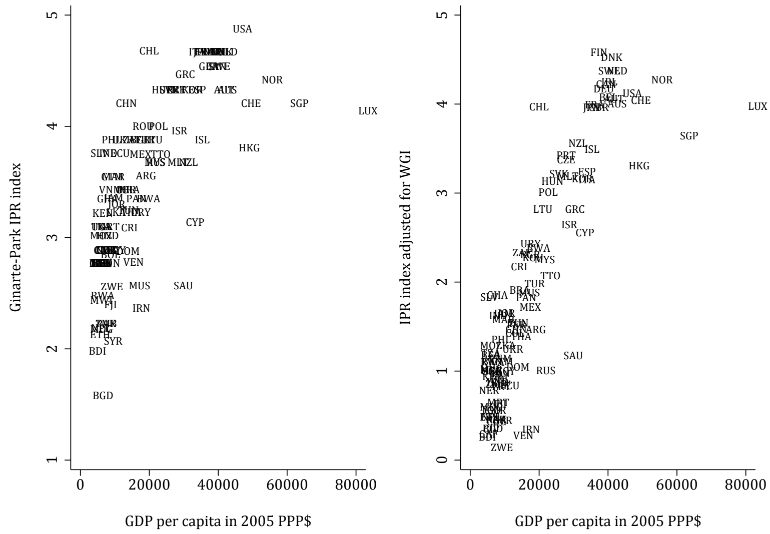
Notes: The classification of the income groups is according to the ranking provided by the World Bank (2011) for year 1990. Countries with income per capita less than $610 are classified as low-income, the income range for the mid-income countries is between $611 and $7620, and high-income countries are those with income per capita larger than $7620.

5.2.3 De jure versus de factor IPR protection

Despite being the most preferred index to use in empirical research, the G-P index also has a major limitation in that it is a de jure measure, reflecting laws and agreements,

[3] By consulting the legal text of each country's patent laws, Rapp-Rozek made a rough and rather subjective assessment of their conformity with the minimum standards proposed as guidelines by the U.S. Chamber of Commerce. More specifically, countries are assigned a score based on their 1984 patent system: 0= No patent laws, 1= Inadequate protection laws, no law prohibiting piracy, 2= Seriously flawed laws, 3= Flaws in law, some enforcement law, 4= Generally good laws, and 5= Protection and enforcement laws fully consistent with the minimum standards proposed by the United States Chamber of Commerce (1987).

Figure 5.1: De Jure versus De Factor IPR Indexes in 2010



rather than the actual, de facto, degree of enforcement in the country. In one of the robustness analyses, we try to correct for the degree of enforcement of patent laws in the country by using data on the World Governance Indicators (World Bank, 2015b).[4] It seems plausible that there is a positive correlation between a country' governance strength and IPR protection enforcement. If the governance of a country is completely ineffective, then de facto IPR protection is likely to be absent regardless of the degree of protection indicated by the G-P index (i.e. de jure protection). Given that the WGI consist of six indicators and each indicator ranks the countries on a scale from 0–100, we take an unweighted average of these six components and divide the final composite score by 100. This means that we obtain a scaling factor ranging from 0–1, where a higher value indicates a more effective government and, by assumption, a more effective enforcement of patent laws. We multiply the scaling factor with the original G-P index and denote it as the enforcement-adjusted IPR index (IPR^e).[5] As mentioned, if a country has perfect governance, the scaling factor would be one meaning that the rules written down in the book are strictly enforced ($IPR^e = IPR^{GP} \times 1$). On the contrary, if the governance of a country is completely ineffective, the scaling factor is zero and the enforcement-adjusted IPR index would be zero as well regardless of the value of de

[4] The World Governance Indicators consist of six indicators: voice and accountability, political stability and absence of violence, control of corruption, government effectiveness, regulatory quality, and rule of law.

[5] In our sample, the country with the highest composite governance score is Finland (0.98), followed by Denmark and New Zealand. On the other hand, Somalia, Iraq, and Myanmar have the worst record of governance in the world.

5

jure IPR protection ($\mathrm{IPR}^{\mathrm{e}} = \mathrm{IPR}^{\mathrm{GP}} \times 0$). For illustrative purposes, we plot these two indexes in Figure 5.1 where the left panel shows de jure IPR protection indicated by the G-P index and the right panel presents de facto IPR protection approximated based on data on the quality of governance. As shown in the figure, the U.S. has the highest de jure IPR protection while the Scandinavian countries have the highest de facto IPR protections.[6] Another noticeable feature of Figure 5.1 is that there is a much greater variation in the enforcement-adjusted index than in the de jure index.

5.2.4 Data on imports

The data on imports are retrieved from the United Nations Commodity Trade Statistics Database (UN Comtrade, 2015). The time series of the data spans from 1962-2014 and the trade commodities are classified by product categories according to three different versions of the Standard International Trade Classification (i.e. SITC Rev.1, Rev.2, Rev.3, respectively). Each classification corresponds to a different time span of data availability.[7] Since SITC Rev.1 is too outdated to link products to industries based on International Standard Industry Classification (ISIC) and data in SITC Rev.3 is available for a much shorter time span, we opt for the commodity classification based on SITC Rev.2 at 4-digit for a sample of 119 countries. Given the nature of IPR index data, the trade data–denominated in U.S. dollars–is also collected every 5 years over the period 1976-2010.[8] Thus, the data used in analysis cover the following years: 1976, 1980, 1985, 1990, 1995, 2000, 2005, and 2010.

The value of the world's total imports has proliferated between 1976 and 2010. For our sample of countries, the value has increased by more than 25 times. If countries are grouped into three different income levels, the low-income countries are found to have increased their imports value most followed by the middle-income. In addition, among 18 different product categories the imports value has grown most for Communication equipment, Computing machinery and Pharmaceuticals.

[6] The correlation between the G-P index and the enforcement-adjusted index is above 0.86. This high correlation suggests that relying on the standard, de jure, measure of IPR protection is not likely to lead to a substantial estimation bias, despite the fact that this measure may overstate the true IPR stringency.

[7] Trade data classified by SITC Rev.1, Rev.2 and Rev.3 are available, respectively, from 1962, 1976, and 1988 onwards.

[8] To increase the number of observations by including the year 1976, it is assumed that the value of the G-P index in 1976 is the same as in 1975. By doing so, the trade data could then be matched with the IPR index from 1976 onwards, instead of 1980. As a robustness check, analysis based on the more restrictive sample is also performed. Results and findings remain consistent (available upon request), though the exact magnitude of the coefficients differ somewhat.

5.2.5 R&D intensity across product categories

What is the technology intensity of a product? Standard practice is to trace the R&D intensity of the industry producing the good as product-level information is generally not available. Thus, we link products (say computers) to industries (in this case Office, accounting and computing machinery) and measure the technology intensity of a product category according to their corresponding industry R&D expenditures. The industry indicator for R&D intensity is only available at the level of 18 product groups, together covering all manufacturing products. This data is retrieved from the OECD STAN Database for Structural Analysis for a sample of 33 countries and over the period 1987-2009. Industries are classified according to ISIC Revision 3 (ISIC Rev.3) and the intensity value is calculated as the share of R&D expenditures in total value added. Thanks to the concordance codes provided by Affendy, Yee and Satoru (2010), the product categories based on SITC Rev.2 classification can be directly linked to manufacturing industries classified by ISIC Rev.3.

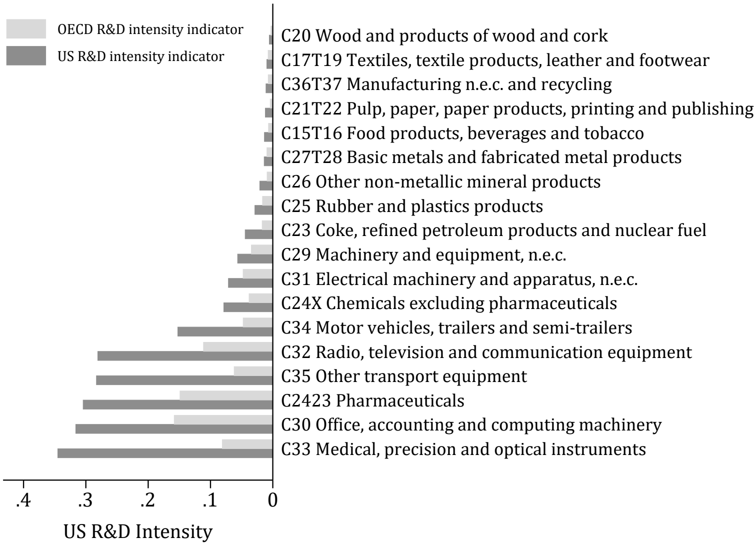
Given that the variation of R&D intensity in an industry over time is rather limited, it seems sensible to smooth out the time variation (i.e. $\mathrm{RD} = \sum \mathrm{RD_t}/\mathrm{T}$). In addition, we follow Rajan and Zingales (1998) in using the values for the U.S. as the baseline proxy for the other countries, as the data is generally of a better quality. While the actual R&D intensity value of a product group differs from country to country, what really matters is the ranking of product groups based on those intensity values.[9] That is, regardless of the size of the intensity values Pharmaceuticals are likely to be R&D intensive products relative to other products in other parts of the world just as in the U.S.; while Textiles, in comparison, will be R&D non-intensive across the globe.

As a robustness check, we also consider using all the data that are available from the OECD STAN database and take an unweighted average of the R&D intensity values for the entire sample of OECD countries. Figure 5.2 provides an overview of the distribution of the product categories with varying degrees of R&D intensity. As anticipated, the majority of the product categories have a similar ranking between the two indicators but the size of the intensity values is noticeably smaller in the OECD indicator. For instance, the R&D intensity value of Computing machinery (industry code C30) of the OECD indicator is only about half of the value of the U.S. indicator (0.15 versus 0.3). As will be discussed later, despite the differences in intensity values, results remain qualitatively consistent.

In addition to using the continuous approach, it is also helpful to consider splitting

[9]Though relying only on rankings would affect the quantitative implications of our estimates.

Figure 5.2: Ranking of R&D Intensity by Product Categories



product categories into two major groups: R&D intensive versus R&D non-intensive as in Ivus (2010). The rationale behind this is the following. If most of the variations are between the two groups, the magnitude of the effect should then remain similar to the continuous approach where IPR is interacted with the R&D intensity value of each product category. However, if product categories are highly heterogeneous, then treating different product categories as homogeneous in a group is likely to significantly underestimate the differential effect. As a standard practice, the product groups are split at the median value of R&D intensity (i.e. C29 in both rankings).

5.3 Empirical results

In this section we discuss the main empirical findings with first results of de jure IPR protection and its robustness to alternative specifications, followed by a comparison with the results of de factor IPR protection. By splitting the analysis into different time periods and dividing importing countries into different income groups, we then study where is the differential effect mostly concentrated. Finally, we discuss the results of splitting imports by country of origin.

5.3.1 Analysis based on the full sample

The results for equation (5.1) using the baseline U.S. R&D intensity indicator and the ordinary least squares (OLS) estimator are presented in the first column of Table 5.2 where the coefficient β is, as anticipated, positive and highly significant. This suggests that for more R&D intensive products, the impact of more stringent IPR protection is significantly larger than products that embody little R&D or technology. This coefficient implies that if a country increases its IPR protection, the imports value will increase by 22% more for a product category at the 90th percentile of R&D intensity (Office, accounting and computing machinery) than for products at the 10th percentile (Textiles, leather and footwear).[10]

Since a few product categories have very large R&D intensity values, it seems sensible to check whether the results are driven by any specific product categories. As shown in the lower panel of Table 5.2, excluding any single product category at a time does not qualitatively affect the results. There are, however, two product categories that warrant further explanation, as the exclusion of these two categories affects the magnitude of the results most significantly. First, after excluding the Pharmaceuticals (C2423) the size of the differential effect became much more pronounced than the baseline specification in which all the product categories are pooled together. This increase in the magnitude seems to imply that imports of Pharmaceuticals may not be that sensitive to IPR protection as the R&D intensity value predicts. This finding is consistent with the work of Delgado, Kyle and McGahan (2013) who find that the impact of IPR protection on imports of Pharmaceuticals is relatively low because merely copying Pharmaceutical products is not likely to be successful in capturing the market shares as complementary resources in distribution also play a significant role. In addition, according to Cohen, Nelson and Walsh (2000) the Pharmaceutical industry relies most heavily on secrecy in protecting its product innovations rather than patent protection. In contrast, there is a sizable drop in the magnitude of the differential effect after excluding Computing machinery (C30). This might be because electronic products are relatively easier to imitate or copy through reverse engineering. Therefore, relative to other product categories imports of Computing machinery are particularly sensitive to changes in IPR protection and leaving it out from the analysis would significantly weaken the underlying differential effect.

These results remain robust when the alternative OECD R&D intensity indicator is used for analysis (column 2, Table 5.2). As before, the exclusion of Pharmaceuticals

[10]This is calculated as: $\hat{\beta} \cdot (\mathrm{RD}^{90\mathrm{th}} - \mathrm{RD}^{10\mathrm{th}})$. Plugging in the values, the differential effect of IPR between these two product categories becomes: 0.718 $\times$ (0.316-0.0096)=22%.

Table 5.2: THE DIFFERENTIAL EFFECTS OF IPR ON IMPORTS

	(1) IPR × RD^{US}	(2) IPR × RD^{OECD}	(3) IPR × Group
All product categories combined	0.718*** (0.087)	1.689*** (0.251)	0.084*** (0.023)
Excluding			
C20 Wood and products of wood	0.882*** (0.085)	2.111*** (0.248)	
C17T19 Textiles, leather, footwear	0.800*** (0.089)	1.876*** (0.256)	
C36T37 Manufacturing n.e.c.	0.792*** (0.089)	1.862*** (0.255)	
C21T22 Paper, printing, publishing	0.702*** (0.091)	1.642*** (0.261)	
C15T16 Food, beverage, tobacco	0.635*** (0.089)	1.471*** (0.256)	R&D non-intensive
C27T28 Basic and fabricated metal	0.696*** (0.091)	1.626*** (0.258)	
C26 Other non-metallic minerals	0.666*** (0.089)	1.550*** (0.257)	
C25 Rubber and plastic products	0.723*** (0.087)	1.692*** (0.255)	
C23 Coke and petroleum products	0.694*** (0.087)	1.623*** (0.251)	
C29 Machinery and equipment	0.692*** (0.088)	1.651*** (0.251)	
C31 Electrical machinery	0.713*** (0.088)	1.694*** (0.251)	
C24X Chemicals excl. pharms	0.703*** (0.088)	1.667*** (0.252)	
C34 Motor vehicles and trailers	0.732*** (0.087)	1.694*** (0.251)	
C32 Radio, TV and communication	0.644*** (0.094)	1.475*** (0.274)	R&D intensive
C35 Other transport equipment	0.720*** (0.093)	1.650*** (0.253)	
C2423 Pharmaceuticals	0.956*** (0.089)	2.868*** (0.247)	
C30 Computing machinery	0.455*** (0.089)	0.651** (0.274)	
C33 Medical instruments	0.704*** (0.106)	1.577*** (0.260)	

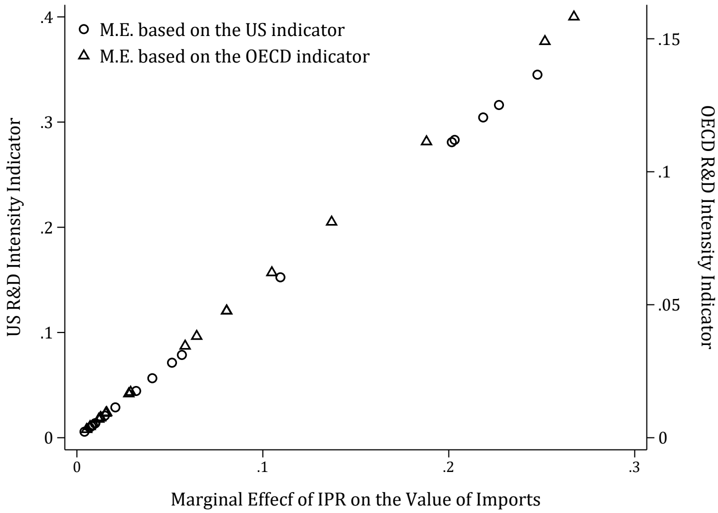
Notes: Column (1) uses R&D intensity indicator based on the U.S. values. Column (2) uses the alternative R&D intensity indicator by taking an unweighted average across all OECD countries and over the period 1987-2009. Column (3) splits the product categories into two major groups: R&D intensive versus R&D non-intensive. All specifications include the country-year and the product-year fixed effects. The model-of-fit, R^2, is about 0.93 across all specifications. The number of observations ranges from a full sample of 11,916 observations to 11,254 observations by omitting one product category at a time. Standard errors shown in parentheses are heteroskedastic robust to country-industry clustering. *** p<0.01, ** p<0.05, * p<0.1.

leads to a stronger differential effect, and the exclusion of Computing machinery leads to a significantly weaker effect. Whereas, dropping any other product category one at a time has modest impact on the quantitative results. Note that the coefficient estimate β appears to be over twice as large when the OECD intensity indicator is used (1.69

versus 0.72), but this does not imply that the differential effect of IPR is doubled. Since the difference-in-differences approach captures a differential effect rather than a main effect, it is more informative to examine the marginal effect of IPR in relation to the associated R&D intensity values.

As shown in Figure 5.3 where 18 product categories are denoted by circles or triangles, depending on the intensity indicator used, the magnitude of the marginal effect remains very similar between the two intensity indicators.[11]

Figure 5.3: Comparing the Size of the Marginal Effects



The results also remain qualitatively consistent when product categories are split into R&D-intensive and R&D non-intensive groups (see column 3 of Table 5.2). The coefficient remains significantly different from zero and taking the estimate at face value, this suggests that more stringent IPR protection leads to an 8 percent faster increase in the value of imports for the R&D-intensive product group than for the R&D non-intensive group. Comparing this finding to the prior results obtained under the continuous approach where the differential effect for a R&D intensive product category and a R&D non-intensive one could be as large as 22 percent, this difference in the magnitude suggests that omitting product-specific variations in terms of technology content, as measured by R&D intensity, would drastically underestimate the size of the differential impact of IPR protection on manufacturing imports. Moreover,

[11]To be precise, the differential effect for a product category at the 90th percentile of R&D intensity and one at the 10th percentile, measured by OECD intensity indicator, is approximately 24 percent. This is very similar to the 22 percent obtained when the U.S. R&D intensity indicator is used.

5

as noted earlier the import sensitivities differ highly between Computing machinery and Pharmaceuticals, even though both of them are classified as R&D intensive products. Pooling them into one single group could not uncover such large within-group differences.

5.3.2 Additional analyses

So far, the discussion of the results has been centred around the effect of de jure IPR protection. In the first column of Table 5.3, we show that the baseline result, from column (1) of Table 5.2, do not change, both qualitatively and quantitatively, if the alternative de factor IPR index is used for analysis.[12] This suggests that the prior results obtained under de jure IPR protection are not likely to be biased due to mismeasurement of the true stringency of IPR protection.

To gain further insights, we split the analysis into different time periods. If imports of technology-intensive products are truly more sensitive to the stringency of IPR protection as the theory predicts, it is likely to observe the differential effect to be more pronounced after 1995, the year in which the world started to rapidly improve IPR protection as mandated by the TRIPs agreement. The reason for this is that as the world improves IPR protection, there is a greater incentive to develop new and improved products that are more technologically-advanced. As a result, the technology content of the products would increase and therefore the sensitivity to changes in IPR protection is likely to be higher as well.[13] As shown in column (2) of Table 5.3, the differential effect is present in both pre- and post-TRIPs time periods, suggesting that the qualitative results are not sensitive to the choice of time intervals. The size of the effect, however, is close to four times larger in the latter than the former period. This finding seem to support the notion that the TRIPs agreement enhances trade and it is especially conducive to trade in knowledge-intensive products. If we divide the sample of importing countries by income groups (see the Appendix Table 5.4 for the full classification of countries by income groups), we show that the effect is the highest among middle-income countries, while there is no significant effect for high-income and low-income countries (column 3, Table 5.3). Since the middle-income countries improved their IPR most during the period of investigation and the improvement in IPR of high-income and low-income

[12]The amount of observations decreases because the World Governance Indicators are only available from 1996 onwards.

[13]Note, the increase in the technology content of the products does not necessarily mean the technology intensity, as measured by the share of R&D expenditures in total value added, would increase as well, as the increase in R&D expenditures is likely to be accompanied by an increase in value added. Moreover, the increase in technology content of the products is likely to be disproportionately more towards products that are R&D intensive relative to products that require little R&D.

Table 5.3: Additional Analyses

	(1) $IPR^e \times RD^{US}$	(2) $IPR \times RD^{US}$	(3) $IPR \times RD^{US}$	(4) $IPR^c \times RD^{US}$	N	R^2
All combined	0.704*** (0.069)				7,556	0.929
Pre–TRIPs		0.266** (0.118)			4,360	0.913
Post–TRIPs		1.010*** (0.093)			7,556	0.929
Imported by						
High-income			-0.064 (0.243)		3,150	0.943
Mid-income			0.490*** (0.163)		5,822	0.896
Low-income			0.098 (0.250)		2,944	0.900
Imports from						
High-income				0.107 (0.134)	11,145	0.868
Mid-income				0.539*** (0.194)	11,117	0.818
Low-income				0.251 (0.221)	10,896	0.805

Notes: Column (1) applies the 'enforcement-adjusted' IPR index by using data from the World Governance Indicators. Column (2) splits the analysis into pre-TRIPs and post-TRIPs time periods. That is, 1976-1990 versus 1995-2010. Column (3) distinguishes importing countries between high-income, mid-income and low-middle income countries. The distinction is according to 1990 GNP per capita provided by the World Bank (2011). Column (4) splits the origin of imports into high-income, low-income and middle-income country groups. All specifications include the country-year and the product-year fixed effects. Standard errors shown in parentheses are heteroskedastic robust to country-product clustering. *** p<0.01, ** p<0.05, * p<0.1.

countries is relatively modest (see Table 5.1), this seems to imply that it is not the absolute level of IPR protection that helps countries to import technology-intensive products but it is the level of protection relative to the other countries.

Since close to 60 percent of the world's total patent applications originate from high-income economies (WIPO, 2015), exports from these countries are more likely to have knowledge embodied than exports from the rest of the world. Thus, it seems probable that the differential effect should be most prominent for imports sourced from high-income countries. In column (4) of Table 5.3, we split imports by the origin of three different income groups and we find that the differential effect is not present for imports coming from high-income countries, but only present for imports from middle-income countries.[14] One possible explanation for this could be that the market expansion effect and the market power effects are cancelled out for imports coming from high-income economies. This finding, in fact, also resembles one of the results of Awokuse and Yin (2010) in their analysis of China' imports. Another possible explanation could also be that the final production stage (and thus gross exports) of technology-intensive products are increasingly taking place in middle-income, rather than high-income countries. International production fragmentation has rapidly increased since the 1990s, in particular in producing high-tech goods such as machinery and electronics (Timmer et al., 2014).

5.4 Conclusions

This chapter is the first to rigorously examine whether increased intellectual property rights (IPR) protection has a larger impact on imports of more R&D-intensive products. Employing a large panel data and the difference-in-differences approach pioneered by Rajan and Zingales (1998), we find that the impact of strengthening IPR protection is significantly stronger for imports of more technology-intensive products. The estimates imply that more stringent IPR protection leads to an increase in the value of imports by 22 percent higher for products at the 90th percentile of R&D intensity (Computing machinery) relative to products at the 10th percentile (Textiles, leather, and footwear). This finding is robust to alternative measures of R&D intensity of product categories and to using a modified IPR index that corrects for the potential enforcement bias of patent protection in the country.

Another major finding of this study is that the product categories are highly heterogenous in their responsiveness to changes in IPR protection. The dichotomous approach, i.e. classifying products into technology intensive and non-intensive groups, used in previous studies (e.g. Ivus, 2010) is unable to reveal such large differences within the group and is likely to significantly underestimate the magnitude of the differential effect of IPR on imports.

The differential effect is also found to be more prominent in the post-TRIPs period and in imports by the middle-income countries. This seems to suggest that by conforming

[14]This finding remains valid if we split the origin of imports into OECD and non-OECD countries. Results available upon request.

to the minimum standards of intellectual property protection set out by the World Trade Organisation, the middle-income countries have benefited most in importing technologically advanced products. By splitting the origin of imports into high-, middle- and low-income countries, we find that the majority of R&D intensive imports do not originate from high-income countries as one would expect, but they originate from its own middle-income group of countries. We have argued that this finding could mean that (1) the market expansion and market power effects are cancelled out for imports coming from advanced economies; or (2) that the production of some technology intensive products (e.g. Electronics) increasingly takes place in middle-income, rather than high-income countries due to international production fragmentation. Irrespective of the underlying cause, this result seems to imply that by strengthening IPR protection the middle-income countries have succeeded in attracting more technology-intensive products from other middle-income countries.

Like most of the previous studies, a major limitation of this chapter is that we cannot disentangle whether the increase in imports value is due to increase in the quantity of products traded or in prices of the products. To the extent that the rise in the value of imports is driven by a higher unit price rather than a larger amount of quantity traded, we may have erroneously interpreted the presence of market power effect as a market expansion effect which would harm rather than enhance trade. This is an area for future research once more detailed data on product-specific prices have become available.

Appendix

Table 5.4: LIST OF COUNTRIES BY INCOME GROUPS

High-income	**Mid-income**		**Low-income**	
Australia	Algeria	Malaysia	Bangladesh	Somalia
Austria	Angola	Malta	Benin	Sri Lanka
Belgium	Argentina	Mauritius	Burk. Faso	Sudan
Canada	Bolivia	Mexico	Burundi	Tanzania
Cyprus	Botswana	Morocco	Cent. Afr. Rep	Togo
Denmark	Brazil	Nicaragua	Chad	Uganda
Finland	Bulgaria	P.N. Guinea	China	Vietnam
France	Cameroon	Panama	Egypt	Zambia
Germany	Chile	Parage	Ethiopia	
Hong Kong	Chile	Peru	Ghana	
Iceland	Congo	Philippines	Guyana	
Ireland	Costa Rica	Poland	Haiti	
Israel	Czech Rep.	Portugal	Honduras	
Italy	Dominica Rep.	Romania	India	
Japan	Ecuador	Russia	Indonesia	
Luxembourg	El Salvador	S. Africa	kenya	
N. Zealand	Fiji	Saudi Arabia	Liberia	
Netherlands	Gabon	Senegal	Madagascar	
Norway	Greece	Slovakia	Malawi	
Singapore	Grenada	Swaziland	Mali	
Spain	Guatemala	Syria	Mauritania	
Sweden	Hungary	Thailand	Mozambique	
Switzerland	Iran	Trinidad & Tobago	Myanmar	
Taiwan	Iraq	Tunisia	Nepal	
U.K.	Ivory Coast	Turkey	Niger	
U.S.A.	Jamaica	Ukraine	Nigeria	
	Jordan	Uruguay	Pakistan	
	Korea	Venezuela	Rwanda	
	Lithuania	Zimbabwe	Sierra Leone	

Notes: The classification of the income groups is according to the ranking provided by the World Bank (2011) for year 1990. Countries with income per capita less than $610 are classified as low-income, the income range for the mid-income countries is between $611 and $7,620, and high-income countries are those with income per capita larger than $7,620.

CHAPTER 6

Samenvatting (Summary in Dutch)

Het begrijpen van de drijvers van economische groei en inkomensverschillen tussen de landen is een kerngebied van economisch onderzoek. Sinds het neoklassieke groeimodel werd ontwikkeld door Solow (1956) en Swan (1956) hebben economen geprobeerd om onderscheid te maken tussen twee ogenschijnlijke oorzaken van de economische groei en inkomensverschillen: factor accumulatie en totale factor productiviteit (TFP). TFP duidt de verschillen in productie aan nadat rekening is gehouden met verschillend gebruik van productiefactoren zoals arbeid en fysiek kapitaal. De heersende aanname dat TFP het grootste deel van de economische groei en de inkomensverschillen tussen landen verklaart wordt op de proef gesteld want de moderne economie, gekenmerkt door het wijdverbreide gebruik van informatie- en communicatietechnologie (ICT), verandert snel. ICT faciliteert talrijke complementaire innovaties die de productiviteit verhogen door vermindering van kosten, ontwikkeling van nieuwe producten, of de verbetering van de immateriële aspecten van de bestaande producten (Brynjolfsson en Hitt, 2000). Als gevolg hiervan zijn de bedrijfsinvesteringen in de traditionele activa, zoals machines en gebouwen, minder belangrijk geworden. In plaats daarvan worden steeds meer middelen verschoven naar investeringen in op kennis gebaseerde immateriële activa, zoals productontwerp, marketing, research en development (R&D) en managementpraktijken, die steeds meer worden gezien als de belangrijkste bronnen van waardecreatie voor ondernemingen. Volgens Hulten (2010) valt de waarde van sommige wereldwijde toonaangevende bedrijven, zoals Microsoft, grotendeels toe te schrijven aan zijn immateriële activa. De stijgende trend in deze nieuwe soorten investeringen suggereert dat de standaard empirische analyse van economische groei op basis van de traditionele productiefactoren (d.w.z. arbeid en fysiek kapitaal) een belangrijk deel van de investeringen in de 21e eeuw mist en daarom niet meer geschikt is voor het begrijpen van de aanjagers van moderne economische groei.

In het afgelopen decennium is er een nieuwe literatuur ontstaan die als doelstelling heeft om de manier waarop bedrijfsactiviteiten worden beschreven in de macro-economische gegevens en analyses te veranderen. Dit wordt gedaan door een verbreding van het investeringsconcept boven de uitgaven aan fysieke activa. Er wordt gesteld dat zolang huidige middelen worden aangewend om te voorzien in *toekomstige* in plaats van *huidige* consumptie, dan moeten al deze uitgaven, hetzij aan materiële of immateriële activa, worden gekapitaliseerd en opgenomen in het bruto binnenlands product (bbp) van een land als de bedrijfsinvesteringen (Corrado, Hulten en Sichel, 2005). Dit argument won aan populariteit onder wetenschappers en leidde uiteindelijk tot de ontwikkeling van een brede regeling voor het categoriseren en het meten door het bedrijfsleven immateriële investeringen zodat ze kunnen worden opgenomen in de nationale rekeningen van een land.

Ondanks de behaald vooruitgang in het afgelopen decennium, moet er nog veel worden gedaan om de rol van immaterieel kapitaal in de moderne economische groei beter te begrijpen. Dit proefschrift draagt bij aan dit zich snel ontwikkelende gebied van onderzoek door middel van vier nieuwe studies die elk een ander aspect van immaterieel kapitaal belichten.

Hoofdstuk twee bestudeert het potentiële spillover effect van immaterieel kapitaal. In het geval van R&D zijn dergelijke effecten al lang bekend (Bloom, Schankerman en Van Reenen, 2013; Griliches, 1992). Echter, investeringen in R&D zijn niet de enige bron van kennis-spillovers tussen ondernemingen. Recent onderzoek heeft aangetoond dat kennis-spillovers ook kunnen voortkomen uit een brede set van niet-R&D immateriële activa, met behulp van data op industrie niveau (Goodridge, Haskel en Wallis, 2012a) of data over de gehele economie (Corrado, Haskel en Jona-Lasinio, 2014). Geen eerder onderzoek heeft zich gericht op de mogelijke spillover van investeringen in het zogenaamde organisatie kapitaal, de kennis van management know-how en organisatiestructuren op bedrijfsniveau. Dit ondanks het feit dat het niveau van de onderneming het meest geschikt is voor het analyseren van spillovers, want schattingen op het niveau van de industrie of de hele economie kunnen geen onderscheid maken tussen productiviteitswinst van eigen investeringen en spillovers van andere bedrijven. Een gepast voorbeeld van een dergelijke spillover is Toyota's just-in-time productieproces, dat zich heel snel heeft verspreid naar andere autofabrikanten (Liker en Morgan, 2006). Een ander voorbeeld van de verspreiding van de managementkennis is het build-to-order (BTO) distributiesysteem dat is bedacht door Dell Computers, maar dat werd gekopieerd door veel andere bedrijven zoals BMW (Gunasekaran en Ngai, 2005).

We volgen de micro-economische literatuur (Eisfeldt en Papanikolaou, 2013) en maken gebruik van de verkoop, algemene en administratieve kosten op de winst- en verliesrekening van een bedrijf als benadering voor de investeringen in organisatie kapitaal. Wij verwachten dat bedrijven meer kans hebben om te profiteren van de investeringen van bedrijven met vergelijkbare technologische eigenschappen, terwijl hun winstgevendheid waarschijnlijk het meest te lijden heeft van investeringen in organisatie kapitaal door naaste concurrenten. We volgen de methodologie van Bloom, Schankerman en Van Reenen (2013) voor de empirische analyse. Op basis van een grote steekproef van bedrijfsrekeningen voor 1266 Amerikaanse productiebedrijven over de periode 1982-2011, hebben we geen bewijs gevonden van kennis-spillovers van organisatie kapitaal die de productiviteit of de marktwaarde van technologisch vergelijkbare bedrijven verhogen. Dit gebrek aan bewijs is in tegenspraak met recente studies van Goodridge et al. (2012a) en Corrado et al. (2014), die wel bewijs vonden voor dergelijke spillovers op basis van meer geaggregeerde data. Gezien deze verschillen in bevindingen beargumenteren wij dat kennis-spillovers waarschijnlijk niet voortkomen uit organisatie kapitaal maar uit andere immateriële activa.

In hoofdstuk drie analyseren we de potentiële complementaire relatie tussen investeringen in ICT en immateriële activa. Deze relatie is bestudeerd in micro-economische studies voor Amerikaanse bedrijven (Bloom et al., 2012). Het is echter nauwelijks bekend of deze relatie kan worden gegeneraliseerd naar het macro-economisch niveau, want vergelijkbare informatie over immateriële investeringen op het niveau van de industrie was lange tijd niet beschikbaar voor de meeste landen. Deze vraag is niet alleen interessant op zichzelf, maar het kan ook belangrijk zijn om beter te begrijpen waarom Europa een tragere groei van de productiviteit heeft ervaren dan de VS sinds het midden van de jaren 1990. Voorafgaande studies van Basu et al. (2004) en Corrado et al. (2014) zijn twee eerste pogingen tot een macro-economische analyse. We dragen verder bij aan deze literatuur door gebruik te maken van recente ontwikkelde gegevens over immateriële investeringen op industrie-niveau, die een nuttige bron van variatie vormen en daarom kunnen helpen de complementaire relatie tussen immateriële activa en ICT vast te stellen

We onderzoeken of een toename van immaterieel kapitaal de productiviteit sterker verhoogt in ICT-intensieve industrieën dan in industrieën die weinig ICT gebruiken. Deze analyse is gebaseerd op de difference-in-differences methode ontwikkeld door Rajan en Zingales (1998). We gebruiken de data geconstrueerd door Niebel, O'Mahony en Saam (2013) voor een set van tien Europese landen en elf bedrijfstakken over de periode 1995-2007. De resultaten laten zien dat de productie elasticiteit van immaterieel kapitaal significant groter is voor ICT intensieve industrieën. Door verder onderscheid te maken tussen de verschillende soorten immateriële activa, tonen we ook aan dat alleen R&D en organisatie kapitaal een hogere productie elasticiteit in ICT-intensieve industrieën vertonen. Dit is consistent met een groot deel van de eerdere analyses op bedrijfsniveau (Brynjolfsson en Hitt., 2003; Polder, Leeuwen, Mohnen en Raymond, 2010).

In hoofdstuk vier wordt nader onderzoek gedaan naar de rol van immaterieel kapitaal in het verklaren van internationale inkomensverschillen. Deze studie is nieuw omdat de bestaande literatuur voornamelijk is gericht op de rol van het traditionele materieel kapitaal (Caselli, 2005; Easterly en Levine, 2001; Hsieh en Klenow, 2010; Hall en Jones, 1999). Het lijkt aannemelijk dat rijkere landen meer investeren in immateriële activa, waardoor het voor een deel de inkomensvariatie tussen landen kan verklaren.

De analyse in dit hoofdstuk is gebaseerd op een nieuw ontwikkelde database over immateriële investeringen die consistent en internationaal vergelijkbaar is voor een steekproef van 60 economieën. Met deze nieuwe database laten we zien dat het aandeel van de investeringen in immateriële activa in het bbp is gestegen tussen 1995 en 2011. Daarnaast is er een sterk positief verband tussen de mate van economische ontwikkeling van een land en zijn investeringsintensiteit in immateriële activa. Door immaterieel kapitaal als een extra productiefactor toe te voegen aan de analyse kunnen we een aanzienlijk groter deel van de variatie in inkomen tussen landen verklaren dan voorheen. Afhankelijk van de aannames met betrekking tot de productie elasticiteit van de productiefactoren kunnen de waargenomen verschillen in immaterieel kapitaal tot 16 procentpunten meer van de inkomensvariatie verklaren. Deze bevinding is consistent met de voorgaande studies die vinden dat immaterieel kapitaal belangrijk is voor de groei van een land over de tijd (Corrado et al., 2009;. Fukao et al., 2009). In beide gevallen is de rol van TFP kleiner zodra er rekening gehouden wordt met immaterieel kapitaal.

In hoofdstuk vijf bestuderen we in welke mate de bescherming van intellectuele eigendomsrechten gebruikt kan worden als instrument door landen met een laag tempo van investeringen in immateriële activa om kennisintensieve producten via de internationale handel aan te trekken. We benaderen de technologische inhoud van een geïmporteerd product door de mate waarin de oorsprong-industrie investeert in R&D. Daarna volgen we de bredere literatuur om de mate van bescherming van intellectuele eigendomsrechten van een land te meten met behulp van de index scores opgesteld door Ginarte en Park (1997). Om de differentiële effecten van de bescherming van intellectuele eigendomsrechten over productcategorieën vast te stellen met een verschillende mate van technologie intensiteit, passen we opnieuw de difference-in-differences methode toe zoals in hoofdstuk drie. Met behulp van invoergegevens voor een steekproef van 119 landen over de periode 1976-2010 laten we zien dat de impact van de bescherming van intellectuele eigendomsrechten op de invoer significant sterker is voor meer kennisintensieve goederen. Meer specifiek, een verhoging van het niveau van bescherming van intellectuele eigendomsrechten leidt tot een 22 procent snellere stijging van de waarde van de invoer van producten in het 90e percentiel van de R&D-intensiteit dan voor producten in het 10e percentiel.

References

Abramovitz, M. (1956). Resource and output trends in the United States since 1870. *American Economic Review*, *46*(2), 5-23.

Ackerberg, D., Benkard, C. L., Berry, S. & Pakes, A. (2007). Econometric tools for analysing market outcomes. In J. Heckman & E. Leamer (Eds.), *Handbook of Econometrics* (Vol. 6A, pp. 4171 – 4276). Amsterdam: North-Holland.

Affendy, M., Yee, L. & Satoru, M. (2010). Commodity-industry classification proxy: A correspondence table between SITC Revision 2 and ISIC Revision 3. *Journal of International Economic Studies*, *24*, 185-202.

Atkeson, A. & Kehoe, P. (2005). Modelling and measuring organisation capital. *Journal of Political Economy*, *113*(5), 1026-1053.

Awano, G., Franklin, M., Haskel, J. & Kastrinaki, Z. (2010). Measuring investment in intangible assets in the U.K.: Results from a new survey. *Economic and Labour Market Review*, *4*(7), 66-71.

Awokuse, T. & Yin, H. (2010). Does stronger intellectual property rights protection induce more bilateral trade? Evidence from China's imports. *World Development*, *38*(8), 1094-1104.

Bagwell, K. (2007). The economic analysis of advertising. In M. Armstrong & R. Porter (Eds.), *Handbook of Industrial Organisation* (Vol. 3, pp. 1701–1844). Amsterdam: North-Holland.

Balli, H. O. & Sørensen, B. E. (2013). Interaction effects in econometrics. *Empirical Economics*, *45*(1), 583–603.

Barnes, P. (2009). Investment in intangible assets and Australia's productivity growth: Sectoral estimates. *Productivity Commission Staff Working Paper*, *Available for download at http://www.pc.gov.au/research/staff-working/intangible-investment.*

Barro, R. J. & Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, *104*, 184–198.

Basu, S., Fernald, J. G., Oulton, N. & Srinivasan, S. (2004). The case of the missing productivity growth, or does information technology explain why productivity accelerated in the United States but not in the United Kingdom? In M. Gertler & K. Rogoff (Eds.), *NBER Macroeconomics Annual* (Vol. 18, pp. 9–63). The MIT Press.

Becker, G. (1993). *Human capital: A theoretical and empirical analysis, with special reference to education.* Chicago: University of Chicago Press.

Bernstein, J. I. & Nadiri, M. I. (1988). Interindustry R-and-D spillovers, rates of return, and production in high-tech industries. *American Economic Review*, *78*(2), 429-434.

Black, S. & Lynch, L. (2005). Measuring organisational capital in the new economy. In C. Corrado, J. Haltiwanger & D. Sichel (Eds.), *Measuring Capital in the New Economy* (Vol. 65, pp. 205–236). Chicago: University of Chicago Press.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D. & Roberts, J. (2013). Does management matter? Evidence from India. *Quarterly Journal of Economics*, *128*(1), 1–51.

Bloom, N., Sadun, R. & Van Reenen, J. (2012). Americans do IT better: US multinationals and the productivity miracle. *American Economic Review*, *102*(1), 167–201.

Bloom, N., Schankerman, M. & Van Reenen, J. (2013). Identify technology spillovers and product market rivalry. *Econometrica*, *81*(4), 1347–1393.

Bloom, N. & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics*, *122*(4), 1352–1048.

Borgo, M. D., Goodridge, P., Haskel, J. & Pesole, A. (2013). Productivity and growth in U.K. industries: An intangible investment approach. *Oxford Bulletin of Economics and Statistics*, *75*(6), 806–834.

Bresnahan, T. F., Brynjolfsson, E. & Hitt, L. M. (2002). Information technology, workplace organisation, and the demand for skilled labour: Firm-level evidence. *Quarterly Journal of Economics*, *117*(1), 339–376.

Bresnahan, T. F. & Trajtenberg, M. (1995). General-purpose technologies - engines of growth. *Journal of Econometrics*, *65*(1), 83–108.

Brynjolfsson, E. & Hitt, L. M. (2000). Beyond computation: Information technology, organisational transformation and business performance. *Journal of Economic Perspectives*, *14*(4), 23–48.

Brynjolfsson, E. & Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics*, *85*(4), 793–808.

Brynjolfsson, E., Hitt, L. M. & Yang, S. (2002). Intangible assets: How the interaction of computers and organisational structure affects stock market valuations. *Brookings Papers on Economic Activity*, *65*(1), 137–198.

Caselli, F. (2005). Accounting for cross-country income differences. In P. Aghion & S. Durlauf (Eds.), *Handbook of Economic Growth* (Vols. 1, Part A, pp. 679–741). Amsterdam: North-Holland.

Chen, W. & Inklaar, R. C. (2016). Productivity spillovers of organisation capital. *Journal of Productivity Analysis*, *45*(3), 229–245.

Chen, W., Niebel, T. & Saam, M. (2016). Are intangibles more productive in ICT-intensive industries? Evidence from EU countries. *Telecommunications Policy*, *40*(5), 471–484.

Chun, H., Fukao, K., Hisa, S. & Miyagawa, T. (2012). Measurement of intangible investments by industry and its role in productivity improvement utilising comparative studies between Japan and Korea. *RIETI Discussion Paper Series 12-E-037*.

Ciccone, A. & Papaioannou, E. (2010). Estimating cross-industry cross-country models using benchmark industry characteristics. *CEPR Discussion Paper No.8056*.

Co, C. (2004). Do patent rights regimes matter? *Review of International Economics*, *12*(3), 359–373.

Cohen, W. M. & Levinthal, D. A. (1989). Innovation and learning: The two faces of R&D. *Economic Journal*, *99*(397), 569–596.

Cohen, W. M., Nelson, R. R. & Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not). *NBER Working Paper Series, No.7552*.

Colecchia, A. & Schreyer, P. (2002). ICT investment and economic growth in the 1990s: Is the United States a unique case? A comparative study of nine OECD countries. *Review of Economic Dynamics*, *5*(2), 408–442.

Corrado, C. & Hao, J. (2014). Brands as productive assets: Concepts, measurement and global trends. *WIPO Economic Research Working Paper No.13*.

Corrado, C., Haskel, J. & Jona-Lasinio, C. (2014). Knowledge spillovers, ICT and productivity growth. *IZA Discussion Paper No.8274*.

Corrado, C., Haskel, J., Jona-Lasinio, C. & Iommi, M. (2012). Intangible capital and growth in advanced economies: Measurement methods and comparative results. *IZA Discussion Paper No.6733*.

Corrado, C., Haskel, J., Jona-Lasinio, C. & Iommi, M. (2013). Innovation and intangible investment in Europe, Japan, and the United States. *Oxford Review of Economic Policy*, *29*(2), 261–286.

Corrado, C. & Hulten, C. (2010). How do you measure "Technological Revolution?". *American Economic Review*, *100*(2), 99–104.

Corrado, C. & Hulten, C. (2014). Innovation accounting. In D. Jorgenson, S. Landefeld & P. Schreyer (Eds.), *Measuring Economic Sustainability and Progress* (pp. 595–628). University of Chicago Press.

Corrado, C., Hulten, C. & Sichel, D. (2005). Measuring capital and technology: An expanded framework. In C. Corrado, J. Haltiwanger & D. Sichel (Eds.), *Measuring*

Capital in the New Economy (Vol. 65, pp. 114–146). Chicago: University of Chicago Press.

Corrado, C., Hulten, C. & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth*, *55*(3), 661–685.

Dedrick, J., Kraemer, K. L. & Linden, G. (2010). Who profits from innovation in global value chains?: A study of the iPod and notebook PCs. *Industrial and Corporate Change*, *19*(1), 81–116.

Delgado, M., Kyle, M. & McGahan, A. M. (2013). Intellectual property protection and the geography of trade. *Journal of Industrial Economics*, *61*(3), 733–762.

De Loecker, J. (2011). Product differentiation, multi-product firms and estimate the impact of trade liberalisation on productivity. *Econometrica*, *79*(5), 1407–1451.

Denicolò, V. & Zanchettin, P. (2014). What causes over-investment in R&D in endogenous growth models? *Economic Journal*, *124*(581), 1192–1212.

Duguet, E. & Lelarge, C. (2012). Does patenting increase the private incentives to innovate? A microeconomic analysis. *Annals of Economics and Statistics*, *107/108*, 201–238.

Dutz, M., Kannebley, S., Scarpelli, M. & Sharma, S. (2012). Measuring intangible assets in an emerging market economy: An application to Brazil. *World Bank Policy Research Working Paper 6142*.

Easterly, W. & Levine, R. (2001). It's not factor accumulation: Stylised facts and growth models. *World Bank Economic Review*, *15*(2), 177–219.

Edquist, H. (2011). Can investment in intangibles explain the Swedish productivity boom in the 1990s? *Review of Income and Wealth*, *57*(4), 658–682.

Eisfeldt, A. & Papanikolaou, D. (2013). Organisation capital and cross-section of expected returns. *Journal of Finance*, *68*(4), 1365–1406.

Falvey, R., Foster, N. & Greenaway, D. (2009). Trade, imitative ability and intellectual property rights. *Review of World Economics*, *145*(3), 373–404.

Feenstra, R., Inklaar, R. C. & Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, *105*(10), 3150–3182.

Fink, C. & Primo Braga, C. (1999). How stronger protection of intellectual property rights affects international trade flows. *World Bank Working Papers No.2051*.

Foster, L., Haltiwanger, J. & Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, *98*(1), 394–425.

Fukao, K., Miyagawa, T., Mukai, K., Shinoda, Y. & Tonogi, K. (2009). Intangible investment in Japan: Measurement and contribution to economic growth. *Review* *of Income and Wealth*, *55*(3), 717–736.

Ginarte, J. C. & Park, W. G. (1997). Determinants of patent rights: A cross-national study. *Research Policy*, *26*(3), 283–301.

Goodridge, P., Haskel, J. & Wallis, G. (2012a). Spillovers from R&D and other intangible investment: Evidence from U.K. industries. *Imperial College Business School Discussion Paper 2012/9*.

Goodridge, P., Haskel, J. & Wallis, G. (2012b). U.K. innovation index: Productivity growth in U.K. industries. *CEPR Discussion Papers 9063*.

Gould, D. M. & Gruben, W. C. (1996). The role of intellectual property rights in economic growth. *Journal of Development Economics*, *48*(2), 323–350.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, *10*(1), 92–116.

Griliches, Z. (1981). Market value, R&D, and patents. *Economics Letters*, *7*(2), 183–187.

Griliches, Z. (1987). R&D and productivity: Measurement issues and econometric results. *Science*, *237*(4810), 31–35.

Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics*, *94*, 29–47.

Griliches, Z. & Mairesse, J. (1998). Production function: The search for identification. In S. Strom (Ed.), *Econometrics and Economic Theory in the Twentieth Century: The Ragnar Frisch Centennial Symposium.* Cambridge: Cambridge University Press.

Gunasekaran, A. & Ngai, E. W. T. (2005). Build-to-order supply chain management: A literature review and framework for development. *Journal of Operations Management*, *23*(5), 423–451.

Hall, B. H. (2007). Measuring the returns to R&D: The depreciation problem. *NBER Working Paper No.13473*.

Hall, B. H. (2009). Business and financial method patents, innovation, and policy. *Scottish Journal of Political Economy*, *56*(S1), 443–473.

Hall, B. H., Lotti, F. & Mairesse, J. (2013). Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology*, *22*(3), 300–328.

Hall, B. H., Mairesse, J. & Mohnen, P. (2010). Measuring the returns to R&D. In B. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (Vol. 2, pp. 1033–1082). Amsterdam: North-Holland.

Hall, R. E. & Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics*, *114*(1), 83–116.

Harberger, A. (1978). Perspective on capital and technology in less developed countries. In M. Artis & A. Nobay (Eds.), *Contemporary Economic Analysis* (pp. 42–72). London: Croom Helm.

Henderson, R., Jaffe, A. & Trajtenberg, M. (2005). Patent citations and the geography of knowledge spillovers: A re-assessment – comment. *American Economic Review*, *95*(1), 461–464.

Hsieh, C. T. & Klenow, P. J. (2010). Development accounting. *American Economic Journal – Macroeconomics*, *2*(1), 207–223.

Hulten, C. R. (2010). Growth accounting. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (Vol. 2, pp. 987–1031). Elsevier.

Hulten, C. R. & Hao, X. (2008). What is a company really worth? Intangible capital and the market to book value puzzle. *NBER Working Paper No.14548*.

Inklaar, R. C. (2010). The sensitivity of capital services measurement: Measure all assets and the cost of capital. *Review of Income and Wealth*, *56*(2), 389–412.

Inklaar, R. C. & Timmer, M. P. (2013). Capital, labour and TFP in PWT 8.0. *Unpublished manuscript, University of Groningen*.

Ivus, O. (2010). Do stronger patent rights raise high-tech exports to the developing world? *Journal of International Economics*, *81*(1), 38–47.

Jaffe, A. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review*, *76*(5), 984–1001.

Jorgenson, D. W. (1963). Capital theory and investment behaviour. *American Economic Review*, *53*(2), 247–259.

Jorgenson, D. W. & Timmer, M. P. (2011). Structural change in advanced nations: A new set of stylised facts. *Scandinavian Journal of Economics*, *113*(1), 1–29.

Jovanovic, B. (1979). Job matching and the theory of turnover. *Journal of Political Economy*, *87*(5), 970–990.

Kanwar, S. & Evenson, R. (2009). On the strength of intellectual property protection that nations provide. *Journal of Development Economics*, *90*(1), 50–56.

Karabarbounis, L. & Neiman, B. (2014). The global decline of the labour share. *Quarterly Journal of Economics*, *129*(1), 61–103.

Keller, T. & Yeaple, S. R. (2009). Multinational enterprises, international trade, and productivity growth: Firm level evidence from the United States. *Review of Economics and Statistics*, *91*(4), 821–831.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, *42*(3), 752–782.

Klette, T. J. & Griliches, Z. (1996). The inconsistency of common scale estimators when output prices are unobserved and endogenous. *Journal of Applied Econometrics*, *11*(4), 343–361.

Kyle, M. K. & McGahan, A. M. (2012). Investments in pharmaceuticals before and after TRIPS. *Review of Economics and Statistics*, *94*(4), 1157–1172.

Landes, M. R. & Rosenfield, A. M. (1994). The durability of advertising revisited. *Journal of Industrial Economics*, *42*(3), 263–276.

Lev, B. & Radhakrishnan, S. (2005). The valuation of organisation capital. In C. Corrado, J. Haltiwanger & D. Sichel (Eds.), *Measuring Capital in the New Economy* (Vol. 65, pp. 73–110). Chicago: University of Chicago Press.

Levinsohn, J. & Petrin, A. (2000). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, *70*(2), 317–341.

Liker, J. & Morgan, J. (2006). The Toyota way in services: The case of lean product development. *Academy of Management Perspectives*, *20*(2), 5–20.

Liu, Z. (2006). Foreign direct investment and technology spillovers: Theory and evidence. *Journal of Development Economics*, *85*(1-2), 176–193.

Mansfield, E. (1965). Technological changes – stimuli, constraints, returns – rates of return from industrial – Research and Development. *American Economic Review*, *55*(1/2), 310–322.

Marrano, M. G., Haskel, J. & Wallis, G. (2009). What happened to the knowledge economy? ICT, intangible investment and Britain's productivity record revisited. *Review of Income and Wealth*, *55*(3), 686–716.

Marschak, J. & Andrews, W. H. (1944). Random simultaneous equations and the theory of production. *Econometrica*, *13*(1), 143–205.

Maskus, K. E. & Penubarti, M. (1995). How trade-related are intellectual property-rights. *Journal of International Economics*, *39*(3-4), 227–248.

Michaels, G., Natraj, A. & Van Reenen, J. (2014). Has ICT polarised skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, *96*(1), 60–77.

Mincer, J. (1974). *Schooling, experience, and earnings.* New York: Columbia University Press.

Mutreje, P. (2014). Equipment and structures capital: Accounting for income differences. *Economic Inquiry*, *52*(2), 713–731.

Nakamura, L. I. (2010). Intangible assets and national income accounting. *Review of Income and Wealth*, *56*(S1), 135–155.

Niebel, T., O'Mahony, M. & Saam, M. (2013). The contribution of intangible assets to sectoral productivity growth in the EU. *ZEW Discussion Papers No.13-062*.

OECD. (2013a). New sources of growth: Knowledge-based capital. *Available for download at http://www.oecd.org/sti/inno/knowledge-based-capital-synthesis.pdf.*

OECD. (2013b). *Supporting investment in knowledge capital, growth and innovation.* Paris: OECD Publishing.

Olley, S. & Pakes, A. (1996). The dynamics of productivity in the telecommunication equipment industry. *Econometrica*, *64*(6), 1263–1297.

O'Mahony, M. (2012). Human capital formation and continuous training: Evidence for EU countries. *Review of Income and Wealth*, *58*(3), 531–549.

O'Mahony, M. & Timmer, M. P. (2009). Output, input and productivity measures at the industry level: the EU KLEMS database. *Economic Journal*, *119*(538), 374–403.

Park, W. G. (2008). International patent protection: 1960-2005. *Research Policy*, *37*(4), 761–766.

Polder, M., van Leeuwen, G., Mohnen, P. & Raymond, W. (2010). Product, process and organisational innovation: Drivers, complementarity and productivity effects. *UNU–MERIT Working Paper Series 2010–035*.

Prescott, E. C. & Visscher, M. (1980). Organisation capital. *Journal of Political Economy*, *88*(3), 446–461.

Psacharopoulos, G. (1994). Returns to investment in education: A global update. *World Development*, *22*(9), 1325–1343.

Rafiquzzaman, M. (2002). The impact of patent rights on international trade: Evidence from Canada. *Canadian Journal of Economics*, *35*(2), 307–330.

Rajan, R. & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, *88*(3), 559–586.

Rapp, R. T. & Rozek, R. P. (1990). Benefits and costs of intellectual property protection in developing-countries. *Journal of World Trade*, *24*(5), 75–102.

Rodriguez, F. & Jayadev, A. (2010). The declining labour share of income. *Human Development Research Paper 2010/36*.

Roth, F. & Thum, A. E. (2013). Intangible capital and labour productivity growth: Panel evidence for the EU from 1998-2005. *Review of Income and Wealth*, *59*(3), 486–508.

Sakakibara, M. & Branstetter, L. (2001). Do stronger patents induce more innovation? Evidence from the 1988 Japanese patent law reforms. *Rand Journal of Economics*, *32*(1), 77–100.

Schreyer, P. & Pilat, D. (2001). Measuring productivity. *OECD Economic Studies*, *33*, 127–165.

Smith, P. J. (1999). Are weak patent rights a barrier to US exports? *Journal of International Economics*, *48*(1), 151–177.

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, *70*(1), 65–94.

Squicciarini, M. & Le Mouel, M. (2012). Defining and measuring investment in organisational capital: Using U.S. microdata to develop a task-based approach. *OECD Working Paper 2012/5*.

Stiroh, K. J. (2002). Information technology and the U.S. productivity revival: What do the industry data say? *American Economic Review*, *92*(5), 1559–1576.

Stock, J. H. & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. Andrews & J. Stock (Eds.), *Identification and Inference for Econometric Analysis: Essays in Honour of Thomas Rothenberg* (pp. 80–108). Cambridge: Cambridge University Press.

Swan, T. W. (1956). Economic growth and capital accumulation. *Economic Record*, *32*(2), 334–361.

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R. & de Vries, G. J. (2014). Slicing up global value chains. *Journal of Economic Perspectives*, *28*(2), 99–118.

Tronconi, C. & Vittucci Marzetti, G. (2011). Organisation capital and firm performance: Empirical evidence for European firms. *Economics Letters*, *112*(2), 141–143.

UN Comtrade. (2015). United Nations Commodity Trade Statistics Database. *URL: http://comtrade.un.org*.

Van Ark, B., Hao, J. X., Corrado, C. & Hulten, C. (2009). Measuring intangible capital and its contribution to economic growth in Europe. *EIB papers*, *14*(1), 62–93.

Van Ark, B., O'Mahony, M. & Timmer, M. P. (2008). The productivity gap between Europe and the United States: Trends and causes. *Journal of Economic Perspectives*, *22*(1), 25–44.

Weng, Y. H., Yang, C. H. & Huang, Y. J. (2009). Intellectual property rights and U.S. information goods exports: The role of imitation threat. *Journal of Cultural Economics*, *33*(2), 109–134.

WIPO. (2015). Patents. *URL: http://www.wipo.int/ipstats/en/wipi*.

World Bank. (2011). Data on country classification: A short history. *URL: http://go.worldbank.org/U9BK7IA1J0*.

World Bank. (2015a). World Development Indicators. *World Bank Publications*.

World Bank. (2015b). World Governance Indicators. *URL: http://govindicators.org*.